

**ENEE 729T: Topics in Communication  
Information Theoretic Methods in Learning  
Spring 2021**

**TIME/VENUE**

MW 3:30 – 4:50 pm EDT  
ONLINE

**INSTRUCTOR**

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**OFFICE HOURS**

MW 2:00 – 3:15 pm (But please, please make an appointment to avoid idling Zoom sessions.) Also at other times by appointment.

**COURSE WEBSITE** (coming soon)

<http://www.ece.umd.edu/class/enee729T>

**OVERVIEW**

The course covers an assortment of information theoretic methods of interest in statistical inference and learning. Topics include: (i) information geometry leading to the EM algorithm and application to maximum likelihood estimation; (ii) measure concentration methods; (iii) correlated multiarmed bandits including in parameter estimation and probability distribution learning from partially sampled observations (finding an arm or a small set of arms that yield information about other correlated arms); and (iv) data privacy *vs* function computation utility tradeoffs.

**PREREQUISITES**

ENEE 620 (Random processes) or equivalent, ENEE 627 (Information theory), or permission of the instructor.

**COURSE OUTLINE**

**I. Information geometry**

Kullback-Leibler divergence, Pythagorean inequality, I-projection on linear families, iterative algorithm for finding the minimum divergence between two convex sets of distributions, EM algorithm, application to maximum likelihood estimation.

**II. Concentration of measure**

Concentration inequalities as basic tools: Markov, Chebyshev, Chernoff bounding, Hoeffding, Bennett, Bernstein, Efron-Stein, Azuma; Entropy method, tensorization, Han's inequalities for entropy and divergence, log Sobolev inequalities, Vapnik-Chevronenkis dimension and entropy. Some applications.

### III. Correlated multiarmed bandits

Prediction and parameter estimation problems will be considered in which an estimator is able to assess self-reward or -loss based on local measurements but is unaware of the consequences of estimation from unseen measurements. However, correlation among measurements affords a new latitude in learning. Stochastic and nonstochastic (or adversarial) multiarmed bandit problems will be considered.

### IV. Data privacy

Various notions of data privacy: Differential privacy, distribution privacy, divergence-based privacy; data privacy vs function computation utility tradeoffs.

### COURSE GRADE

The course grade will be determined on the basis of individual or (small) team projects and in-class presentations. Specifically, an individual's or a team's performance will be evaluated by means of a (i) a midterm assessment of progress on a term project, and (ii) a final assessment of the completed term project. A term project can consist of (a) work on a chosen or assigned topic involving open issues or (b) a critical examination of a pertinent topic or topics in the existing literature – in both cases combined with a comprehensive oral presentation at the end of the semester.

Problems to be addressed in a term project will be fixed at the end of approximately four (4) weeks into the semester.

### REFERENCES

There is no required or recommended text. The course material will be drawn largely from a selection of books and publications that are listed below. Some of this material will be posted at the course website (marked by (\*)).

#### 0. Sine qua non

The following two classics are shining sources of enlightenment in information theory.

(\*) I. Csiszár and J. Körner, *Information Theory: Coding Theorems for Discrete Memoryless Systems*, Academic, Cambridge U Press, 2011. (A PDF version of the first edition (1981) will be posted at the course website.)

T.M. Cover and J. Thomas, *Elements of Information Theory*, Wiley, New York, 1991.

#### I. Information geometry

D. Barber, *Bayesian Reasoning and Machine Learning*, Chapter 11, Cambridge U Press, 2012.

(\*) I. Csiszár and G. Tusnády, "Information geometry and alternating minimization procedures," *Statistics and Decisions*, Suppl. Issue 1, pp. 205-237, 1984.

(\*) I. Csiszár and P. Shields, "Information Theory and Statistics: A Tutorial," *Foundations and Trends in Communications and Information Theory*, Volume 1, Issue 4, 2004.

(\*) A. Kumar and R. Sundaresan, "Minimization Problems Based on Relative  $\alpha$ -Entropy I: Forward Projection," *IEEE Trans. Information Theory*, vol. 61, no. 9, pp. 5063 - 5080, September 2015.

(\*) A. Kumar and R. Sundaresan, “Minimization Problems Based on Relative  $\alpha$ -Entropy II: Reverse Projection,” *IEEE Trans. Information Theory*, vol. 61, no. 9, pp. 5081 - 5095, September 2015.

S. Shalev-Shwartz and S. Ben-David, *Understanding Machine Learning, From Theory to Algorithms*, Chapter 24, Cambridge U Press, 2014.

## II. Concentration of measure

D. P. Dubhashi and A. Panconesi, *Concentration of Measure for the Analysis of Randomized Algorithms*, Cambridge U Press, 2009.

(\*) S. Boucheron, G. Lugosi and O. Bousquet, “Concentration Inequalities,” *Advances in Machine Learning*, O. Bousquet, U. v. Luxburg and G. Rätsch (Eds.), pp. 208 - 240, Springer, 2004.

(\*) S. Boucheron, G. Lugosi and O. Bousquet, “Introduction to Statistical Learning Theory,” *Advances in Machine Learning*, O. Bousquet, U. v. Luxburg and G. Rätsch (Eds.), pp. 169 - 207, Springer, 2004.

S. Boucheron, G. Lugosi and P. Massart, *Concentration Inequalities*,” Oxford U Press, 2013.

(\*) M. Raginsky and I. Sason, *Concentration of Measure Inequalities in Information Theory, Communications, and Coding*, 3rd Ed., Foundations and Trends in Communications and Information Theory, NoW, 2019.

(\*) I. Sason and S. Verdú, “Arimoto-Rényi Conditional Entropy and Bayesian M-Ary Hypothesis Testing,” *IEEE Trans. Information Theory*, vol. 64, no. 1, pp. 4 - 25, January 2018.

## III. Multiarmed bandits

J. Y. Audibert, S. Bubeck and R. Munos, “Best Arm Identification in Multiarmed Bandits,” *Conference on Learning Theory*, pp. 41 - 53, 2010.

(\*) S. Bubeck and N. Cesa-Bianchi, “Regret Analysis of Stochastic and Nonstochastic Multiarmed Bandit Problems,” <https://arxiv.org/abs/1204.5721v2>.

N. Cesa-Bianchi, and G. Lugosi, *Prediction, Learning, and Games*, Cambridge U Press, New York, 2006.

C. Guestrin, A. Krause, and A. P. Singh, “Near-Optimal Sensor Placements in Gaussian Processes,” *International Conference on Machine Learning*, pp. 265 - 272, 2005.

(\*) S. Gupta, S. Chaudhari, S. Mukherjee, G. Joshi and O. Yagan, “A Unified Approach to Translate Classical Bandit Algorithms to the Structured Bandit Setting,” *IEEE Trans. Information Theory*, vol. 1, no. 3, pp. 840 - 853, November 2020.

(\*) S. Gupta, G. Joshi and O. Yagan, “Best-Arm Identification in Correlated Multiarmed Bandits,” *preprint*, 2020.

(\*) K. Jamieson and R. Nowak, “Best-arm Identification Algorithms for Multiarmed Bandits in the Fixed Confidence Setting,” 2014 48th Annual Conference on Information Sciences and Systems (CISS), Princeton, NJ, 2014, pp. 1-6, doi: 10.1109/CISS.2014.6814096.

E. Kaufmann, O. Cappé and A. Garivier, “On the Complexity of Best Arm Identification in Multiarmed Bandit Models,” *Journal of Machine Learning Research*, 2015.

T. Lattimore and C. Szepesvári, *Bandit Algorithms*, <https://tor-lattimore.com/downloads/book/book.pdf>

C. Y. Liu and S. Bubeck, “Most Correlated Arms Identification,” *Conference on Learning Theory*, pp. 623–637, 2014.

L. A. Prashanth, “Multi-Armed Bandits,” *CS 6046, Course notes*, March 2018.

#### IV. Data privacy

(\*) S. Asoodeh, M. Diaz, F. Alajai and T. Linder, “Estimation Efficiency Under Privacy Constraints,” *IEEE Trans. Information Theory*, vol. 65, no. 3, pp. 1512–1534, March 2019.

(\*) R. Bassily, A. Groce, J. Katz and A. Smith, “Coupled-Worlds Privacy: Exploiting Adversarial Uncertainty in Statistical Data Privacy,” FOCS 2013.

(\*) C. Dwork, “Differential Privacy,” in Bugliesi M., Preneel B., Sassone V., Wegener I. (eds), *Automata, Languages and Programming, ICALP 2006, Lecture Notes in Computer Science*, vol 4052. Springer, Berlin, Heidelberg.

(\*) C. Dwork, F. McSherry, K. Nissim and A. Smith, “Calibrating Noise to Sensitivity in Private Data Analysis,” *Journal of Privacy and Confidentiality* (2016-2017)7, Number 3, 1751.

(\*) Q. Geng and P. Viswanath, “The Optimal Noise-Adding Mechanism in Differential Privacy,” *IEEE Trans. Information Theory*, vol. 66, no. 3, pp. 925–951, February 2016.

(\*) Q. Geng, P. Kairouz, S. Oh and P. Viswanath, “The Staircase Mechanism in Differential Privacy,” *IEEE Journal Selected Topics in Signal Processing*, vol. 9, No. 7, pp. 1176–1184, October 2015.

(\*) C. Huang, P. Kairouz, X. Chen, L. Sankar and R. Rajagopal, “Context-Aware Generative Adversarial Privacy,” *Entropy* 2017, 19, 656, pp. 1–35.

(\*) I. Issa, A. B. Wagner and S. Kamath, “An Operational Approach to Information Leakage,” *IEEE Trans. Information Theory*, vol. 62, no. 2, pp. 1625–1657, March 2020.

(\*) A. Nageswaran and P. Narayan, “Data Privacy for a  $\rho$ -Recoverable Function,” *IEEE Trans. Information Theory*, vol. 65, no. 6, pp. 3470–3488, June 2019.

(\*) A. Smith, “Efficient, Differentially Private Point Estimators,” arXiv:0809.4794v1, Sept. 2008.