a. Matrix concentration inequalities.

* An Introduction to Matrix Concentration Inequalities. J. Tropp. https://arxiv.org/pdf/1501.01571.pdf

b. Concentration inequalities for self-normalized processes.

* (Using the method of mixtures.) Self-normalized processes: exponential inequalities, moment bounds and iterated logarithm laws. Victor H. de la Pena, Michael J. Klass, Tze Leung Lai. https://arxiv.org/abs/math/0410102

* (Using the "peeling" method) Informational Confidence Bounds for Self-Normalized Averages and Applications. Aurelien Garivier. https://arxiv.org/abs/1309.3376

c. Concentration inequalities for empirical processes.

* Variance of empirical processes
* Suprema of empirical processes - Expected values and concentration around the expectation

Course textbook (Boucheron et al)

d. Empirical Bernstein Bounds in machine learning.

* Empirical Bernstein Bounds and Sample Variance Penalization. Andreas Maurer, Massimiliano Pontil. https://arxiv.org/abs/0907.3740

* Tuning bandit algorithms in stochastic environments. Jean-Yves Audibert, Remi Munos, Csaba Szepesvari. http://certis.enpc.fr/~audibert/ucb_alt.pdf

e. Concentration for functions of Markov chains.

* Chernoff-Hoeffding Bounds for Markov Chains: Generalized and Simplified. Kai-Min Chung, Henry Lam, Zhenming Liu, and Michael Mitzenmacher. http://www-personal.umich.edu/~khlam/files/CLLM.pdf

* Concentration inequalities for Markov chains by Marton couplings and spectral methods. Daniel Paulin. https://projecteuclid.org/euclid.ejp/1465067185

f. The Gaussian Isoperimetric theorem.

* Course reference book - Boucheron et al.

* Any other source.

g., h. (multiple projects possible) Applications of Talagrand's convex distance inequality

Any TWO of the following:

1. Stochastic Traveling Salesman Problems (TSP).
2. Length of minimum spanning trees on random graphs.
3. Concentration for certifiable functions.
4. Concentration around the median for convex Lipschitz functions and applications to matrix eigenvalues.
5. Any other instructive application.

(References for 1, 2: Concentration. Colin McDiarmid. http://www.stats.ox.ac.uk/people/academic_staff/colin_mcdiarmid/?a=4139

Reference for 3: The Probabilistic Method. 2nd Edition Noga Alon, Joel H. Spencer.

Reference for 4: Notes on Talagrand's inequalities. Nicholas Cook. http://www.math.ucla.edu/~nickcook/talagrand.pdf)

i. Probably-Approximately-Correct(PAC) Bayes concentration bounds in machine learning.

* PAC-Bayes-Empirical-Bernstein Inequality. Ilya Tolstikhin & Yevgeny Seldin. http://papers.nips.cc/paper/4903-pac-bayes-empirical-bernstein-inequality.pdf

* PAC-Bayes Mini-tutorial: A Continuous Union Bound. Tim van Erven. https://arxiv.org/abs/1405.1580

j,k. Distributed randomized algorithms

*Estimating the average degree of a graph by querying degrees of its vertices. Reference: Feige, "On sums of independent random variables with bounded variance and estimating the average degree in a graph." SIAM J. Comput., Vol. 35, No. 4, pp. 964–984, 2006.

*Distributed edge coloring. Reference: A. Panconesi and A. Srinivasan, "Randomized Distributed Edge Coloring via an Extension of the Chernoff--Hoeffding Bounds," SIAM J. Comput., vol. 26, no.

2, pp. 350–368, 1997.

l. Threshold phenomenon in connectivity for random graphs

* P. Erdos and A. Renyi, On the existence of a factor of degree one of a connected random graph, Acta Math. Acad. Sci. Hung. 17 (1966), 359–368.
* E. Friedgut, Sharp thresholds of graph properties, and the k-sat problem, J. Amer. Math. Soc. 12 (1999), 1017–1054.
* B. Bollobás, Random graphs, 2d ed., Cambridge Univ. Press, 2001.

m. Reed Muller codes achieve capacity of erasure channel

* A new result due to Kudekar et. al. uses the threshold result we discussed in the class to show that Reed–Muller codes achieve the capacity of the Binary Erasure Channel. This settles a long-standing open question. Reference is https://arxiv.org/abs/1601.04689.

n. Noise stability and influence

* The paper titled “Noise stability of functions with low influences: invariance and optimality” by E. Mossel, R. O’Donnell, and K. Oleszkiewicz, FOCS 2005. This paper provides a method for converting probability calculations related to Boolean functions to those involving Gaussian random variables – somewhat opposite to what we did to prove Gaussian log-Sobolev inequality.

* R. O’ Donnell, Analysis of Boolean functions. Cambridge Univ. Press, 2014.

o. Anti-concentration inequalities

*These inequalities bound the probability that a random variable is concentrated in an interval (or a ball). There are several resources available for this material, including excellent notes by Manjunath Krishnapur available at http://math.iisc.ernet.in/~manju/anti-concentration.pdf.

Other topics that may be suggested