Monday May 17

11:15 Mark Meckes

Eigenvalue is not a dirty word.

The last line of the preface to Elizabeth's book is, "If my writing helps to illuminate the ideas I have tried to describe, it is because I got to talk it out first at the breakfast table." I will give a history of the main themes of the mathematical conversations that took place at that breakfast table and made it into our joint works over the years.

12:15 Jon Keating

Joint Moments of Characteristic Polynomials of Random Unitary Matrices

I will review the calculation of the moments of characteristic polynomials of random unitary matrices, and will then describe recent progress in calculating the joint moments of these polynomials and their derivative.

1:45 Kavita Ramanan

Tales of Random Projections of High-dimensional Measures

Properties of random projections of high-dimensional probability measures are of interest in a variety of fields, including asymptotic convex geometry, high-dimensional statistics and data analysis. A particular question of interest is to identify what properties of high-dimensional measures may be captured by its lower-dimensional projections. I will describe what light a large deviations perspective can shed on this question. This line of research was inspired in part by a wonderfully lucid talk given by E. Meckes at the Women in Probability conference at Cornell in 2008.

2:30 Sourav Chatterjee

Gauge-string duality and Elizabeth Meckes's infinitesimal Stein's method

In her thesis, Elizabeth Meckes designed an "infinitesimal version" of Stein's method to produce Stein equations for Haar measures, which she used to analyze properties of Haar measures on Lie groups, among other things. I will talk about an application of this idea to derive a "master loop equation" for lattice gauge theories, which are discrete versions of quantum Yang-Mills theories. The master loop equation leads to a duality between a quantum Yang-Mills theory on the lattice and a discrete string theory.

Tuesday May 18

11:15 Tai Melcher

Improved log Sobolev coefficients for compact Lie groups

It is a now classical result in stochastic analysis that a lower curvature bound on a Riemannian manifold M implies that a log Sobolev inequality holds for the heat kernel measure, that is, the end point distribution of a Brownian motion, on M. In particular, if the curvature is non-negative, the classical result implies that the log Sobolev coefficient is at most linear. Given the relationship between the log Sobolev coefficient and concentration of measure, it should be that one is able to improve this bound for compact manifolds. Using basic properties of Lie groups and Brownian motion, we improve the standard estimate for the log Sobolev coefficients of the heat kernel measure on compact Lie groups of non-negative curvature. We'll use Brownian motion on the Lie group of unitary matrices as our main example.

12:00 Matt Kahle

Limit theorems for Betti numbers of random simplicial complexes.

The topology of random simplicial complexes has been an active area of mathematics for the past 15 years or so. Some of the first papers in the area explored phase transitions for vanishing of homology, or expectations for the Betti numbers (colloquially, the number of k-dimensional holes) . My joint work with Elizabeth Meckes started to explore more a more refined picture of limiting distributions for Betti numbers. In this talk, I will briefly discuss this joint work and one or two of the developments since then. The talk will aim to be self contained, and I will not assume any topological prerequisites.

1:30 Sayan Mukherjee

A Measure-Theoretic Dvoretzky Theorem and Applications to Data Science

The idea of considering random projections of high-dimensional data has a long history in data science. The idea goes back to Tukey in the context of exploratory data analysis and several prominent individuals including Elizabeth's advisor Persi Diaconis have made contributions. In this talk I focus on how random projections have been used in data science including theory, algorithms, and general principles based on random projections. I will start by discussing the notion of random Tukey depth and the data analysis problem that it addressed. I will then discuss the celebrated Johnson-Lindenstrauss lemma and talk about it's impact both algorithmically as well as a proof technique both in data science and the interface of theoretical computer science with machine learning. I will then state the results and some of the key ideas in Elizabeth's paper ``A Measure-Theoretic Dvoretzky Theorem" which states some of the tightest results for random projections. I will then discuss how the ideas in ``A Measure-Theoretic Dvoretzky Theorem" have become relevant in compressive sensing and the high-dimensional probability tools being used to analyze deep neural networks. I will close with a ``theorem" that Elizabeth and I had talked about off and on for several years -- is there a homological version of the Johnson-Lindenstrauss lemma ?