Compressive Sensing with Structured Random Matrices

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Abstract:
The recent theory of compressive sensing predicts that (approximately) sparse vectors can be recovered from vastly incomplete linear measurements using efficient algorithms.
This principle has a large number of potential applications in signal and image processing, machine learning and more. Optimal measurement matrices in this context known so far are based on randomness. Recovery algorithms include convex optimization approaches (l1-minimization) as well as greedy methods. Gaussian and Bernoulli random matrices are provably optimal in the sense that the smallest possible number of corresponding samples are required. Such matrices, however, are of limited practical interest because of the lack of any structure. In fact, applications demand for certain structure because of limited freedom to inject randomness in the measurement process. We present recovery results for various structured random matrices including random partial Fourier matrices and partial random circulant matrices. We will also discuss mathematical techniques for proving such results which are interesting by themselves.
These involve probabilistic bounds for suprema of empirical processes and of chaos processes. If time permits, we will also review recent extensions of compressive sensing for recovering matrices of low rank from incomplete information via efficient algorithms such as nuclear norm minimization.