Theoretical guarantees for generative compressed sensing with subsampled isometries

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In work by Bora et al. (2017), a mathematical framework was developed for compressed sensing guarantees when the measurement matrix is Gaussian and the signal structure is the range of a Lipschitz function (with applications to generative neural networks (GNNs)). We consider measurement matrices derived by sampling uniformly at random rows of a unitary matrix (including subsampled Fourier measurements as a special case). We prove the first known restricted isometry guarantee for compressed sensing with GNNs and subsampled isometries, and provide recovery bounds. Recovery efficacy is characterized by the coherence, a new parameter, which measures the interplay between the range of the network and the measurement matrix. Furthermore, we propose a regularization strategy for training GNNs to have favourable coherence with the measurement operator. We provide compelling numerical simulations that support this regularized training strategy: our strategy yields low coherence networks that require fewer measurements for signal recovery. This, together with our theoretical results, supports coherence as a natural quantity for characterizing generative compressed sensing with subsampled isometries. This poster is based on a recent co-authored publication in IEEE JSAIT.

Joint work with Simone Brugiapaglia (Concordia University, Montreal, Canada), Babhru Joshi (University of British Columbia, Vancouver, Canada), Matthew Scott (University of British Columbia, Vancouver, Canada), Yaniv Plan (University of British Columbia, Vancouver, Canada) and Özgür Yilmaz (University of British Columbia, Vancouver, Canada).