High-dimensional polynomial approximation via compressed sensing – Bibliography

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Abstract

This is a preliminary annotated bibliography on high-dimensional polynomial expansions for computing solutions of parametric PDEs, with a focus on compressed sensing and least squares techniques. It is based on a mini-tutorial I gave at the 2016 SIAM UQ Conference.

This document is a work in progress and contains only a partial list of relevant papers in this area. Please email me (ben_adcock@sfu.ca) with comments, suggestions for additions and updated citation information.

1 Compressed sensing references

1.1 General references

[Foucart and Rauhut, 2013]

Book on compressed sensing theory and techniques.

[Cai and Zhang, 2014]

Proof that the RIP implies stable and robust recovery with the sharp estimate $\delta_{2s} < 1/\sqrt{2}$.

1.2 Uniform recovery results

[Rudelson and Vershynin, 2008]

The RIP for Fourier and Gaussian measurements.

[Rauhut, 2010]

The RIP for bounded orthonormal systems.

[Cheraghchi et al., 2013]

[Haviv and Regev, 2016]

[Chkifa et al., 2015]

Improvements of the log factors in the measurement condition for bounded orthonormal systems to satisfy the RIP.

1.3 Nonuniform recovery results

[Gross, 2011]

The golfing scheme.

[Candès and Plan, 2011]

Nonuniform recovery theorem for recovery of s-sparse vectors without the RIP. Based on coherence of the sampling distribution.

[Adcock and Hansen, 2016]

Nonuniform recovery results in the infinite-dimensional setting for subsampled isometries.

1.4 Miscallaneous

[Friedlander et al., 2012]

[Yu and Baek, 2013]

Compressed sensing with prior support information via weighted ℓ^1 minimization.

2 Polynomial approximation

2.1 Regularity theory

[Cohen et al., 2011]

Regularity estimates for polynomial approximation of parametric elliptic PDEs.

[Tran et al., 2015]

Estimates for quasi-optimal polynomial approximations of parametric PDEs.

2.2 Reviews

[Narayan and Zhou, 2015]

Review of stochastic collocation on unstructured meshes by least squares and compressed sensing.

2.3 Approximation theory

[Migliorati, 2015]

Markov and Nikolskii inequalities for multivariate polynomials on downward closed sets.

3 Discrete least squares for polynomial approximation

3.1 Theory

[Cohen et al., 2013]

Sample complexity estimates in the one-dimensional case.

[Migliorati, 2013]

[Migliorati et al., 2014]

Sample complexity estimates in the multivariate case.

[Migliorati and Nobile, 2014]

Analysis of discrete least squares with low-discrepancy point sets.

3.2 Sampling schemes

[Narayan et al., 2014]

Sampling from the equilibrium measure and Christoffel weighting of the least-squares system.

[Zhou et al., 2015]

Sampling using randomly subsampled Gaussian quadratures.

4 Compressed sensing for polynomial approximation

4.1 ℓ^1 minimization

[Rauhut and Ward, 2012]

One-dimensional Legendre polynomials with preconditioning and Chebyshev sampling.

[Yan et al., 2012]

Multivariate Legendre polynomials with random sampling from the Chebyshev and uniform measures.

[Mathelin and Gallivan, 2012]

[Doostan and Owhadi, 2011]

Application to PDEs with random coefficients.

4.2 Weighted ℓ^1 minimization

[Yang and Karniadakis, 2013]

A reweighted ℓ^1 minimization techniques applied to multivariate polynomial expansions.

[Peng et al., 2014]

Adapted weights based on *a priori* estimates for expansion coefficients.

[Rauhut and Ward, 2013]

Theoretical results on weighted sparsity and weighted RIP for bounded orthonormal systems.

[Adcock, 2015b]

Worst-case recovery guarantees for deterministic samples in one dimensions.

[Adcock, 2015a]

Nonuniform recovery guarantees for weighted ℓ^1 minimization with arbitrary weights. Optimal sample complexity estimates for L^∞ function norm weights.

[Chkifa et al., 2015]

Uniform recovery guarantees for weighted ℓ^1 minimization with L^∞ function norm weights and polynomial approximations in downward closed sets.

4.3 Design of sampling points

[Hampton and Doostan, 2014]

Coherence-optimal sampling.

[Jakeman et al., 2016]

Sampling with respect to the weighted equilibrium measure, with preconditioning via the Christoffel function.

[Tang and Iaccarino, 2014]

[Guo et al., 2016]

Subsampled Gaussian quadratures.

[Xu and Zhou, 2014]

Deterministic interpolation grids based on Weil points.

4.4 Sparsity enhancement

[Jakeman et al., 2014]

Best basis selection technique.

[Yang et al., 2015]

Sparsity enhancement via coordinate rotations.

4.5 Gradient sampling

[Peng et al., 2015]

Compressed sensing for Legendre and Hermite polynomial expansions using function and gradient evaluations

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