Learning Concise Representations for High-Dimensional Data

ABSTRACT

The idea that many important classes of signals can be well-represented by linear combinations of a small set of atoms selected from a given dictionary has had dramatic impact on the theory and practice of signal processing. For practical problems in which an appropriate dictionary is not known ahead of time, it is desirable to be able to learn the dictionary from data. While many successful heuristics exist for this problem, their behavior and working conditions are still largely a mystery. We discuss recent theoretical results characterizing the local optima of this problem, for general (overcomplete) dictionaries. We then show one particular situation in which the problem is globally well posed, and can be solved with an efficient algorithm. Our analysis shows that in a random coefficient model with sufficient sparsity, an unknown square dictionary can be exactly recovered, by solving a sequence of convex programs. We sketch connections to problems of matrix recovery. We show related optimization techniques can be adapted to learn effective representations for imaging tasks such as super-resolution and automatic face recognition, that in some situations admit task-specific performance guarantees.

This talk draws on joint works with Huan Wang and Dan Spielman (Yale), Quan Geng (UIUC), and Yuqian Zhang, Cun Mu and Han-Wen Kuo (Columbia).