

SCALABLE INFERENCE AND RECOVERY FROM COMPRESSIVE MEASUREMENTS



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Overview

Data deluge carries technological challenges:

- acquire, store, and process huge amounts of high-dimensional data

Reduce these burdens by reducing the dimensionality of the data

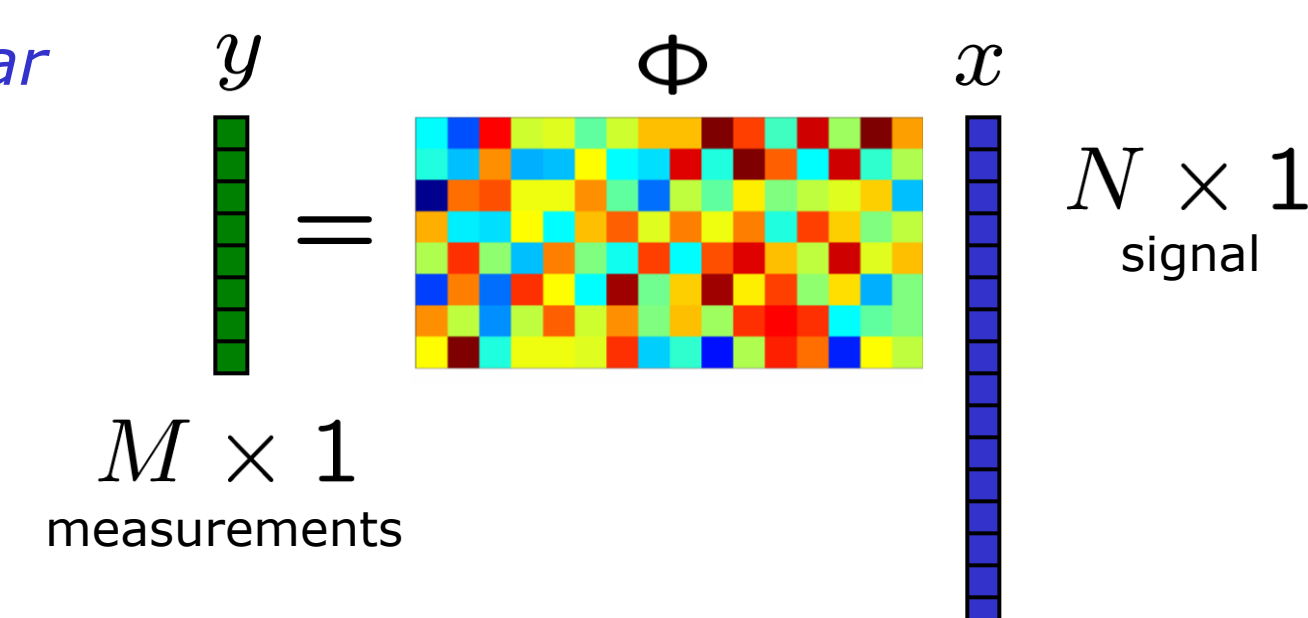
- capture key signal information in a reduced set of measurements
- later recover signal or statistics of interest

Why is dimensionality reduction even possible?

- signals and data may have *low-dimensional structure*,
- statistics of interest may involve *low-complexity inference*,
- or both

Several precedents for using *random, nonadaptive, linear measurements*:

- estimating approximate nearest-neighbors
- estimating statistics of large data sets
- compressed sensing



Common link for success in these applications is a *concentration of measure phenomenon*:

- let $x \in \mathbb{R}^N$ and let $\Phi: \mathbb{R}^N \times \mathbb{R}^M$ be a random matrix with iid Gaussian entries; then

$$P(|\|\Phi x\|_{\ell_2}^2 - \|x\|_{\ell_2}^2| \geq \epsilon \|x\|_{\ell_2}^2) \leq 2e^{-M\epsilon^2/4}$$

- other distributions for Φ also possible

This property has substantial implications in a number of settings

- compressive *hardware* under development

Low-Complexity Inference

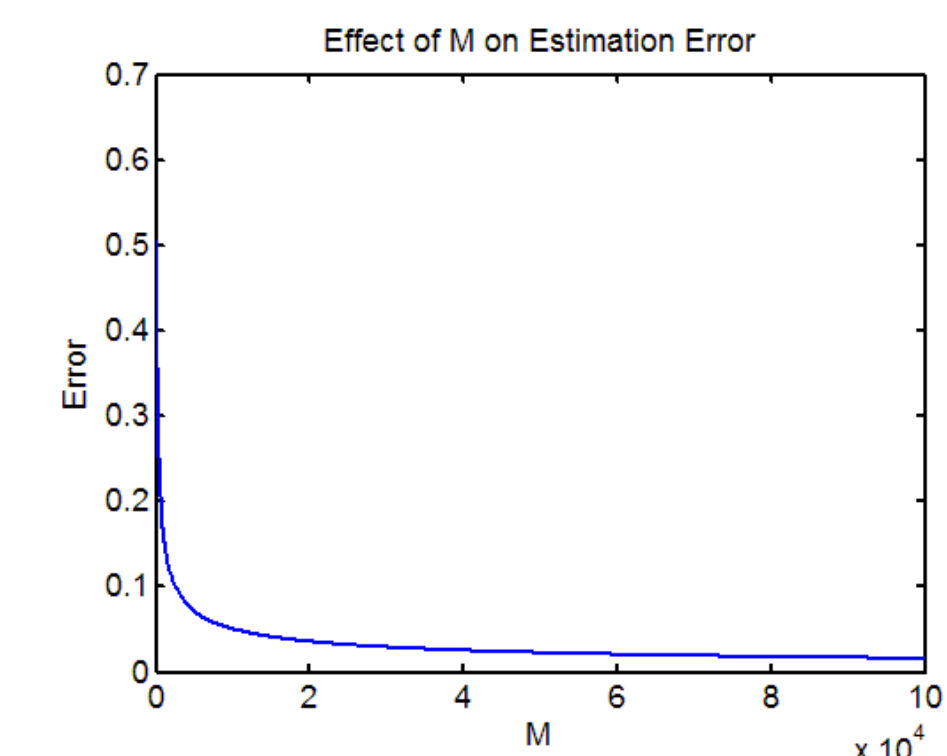
Estimation

Suppose we want to estimate $\langle x, s \rangle$ from $y = \Phi x$

With probability at least $1 - \delta$,

$$|\langle \Phi x, \Phi s \rangle - \langle x, s \rangle| \leq \kappa_\delta \frac{\|x\|_2 \|s\|_2}{\sqrt{M}}$$

where $\kappa_\delta = 2\sqrt{12 \log(\frac{6}{\delta})}$.



Detection

Suppose we want to determine between

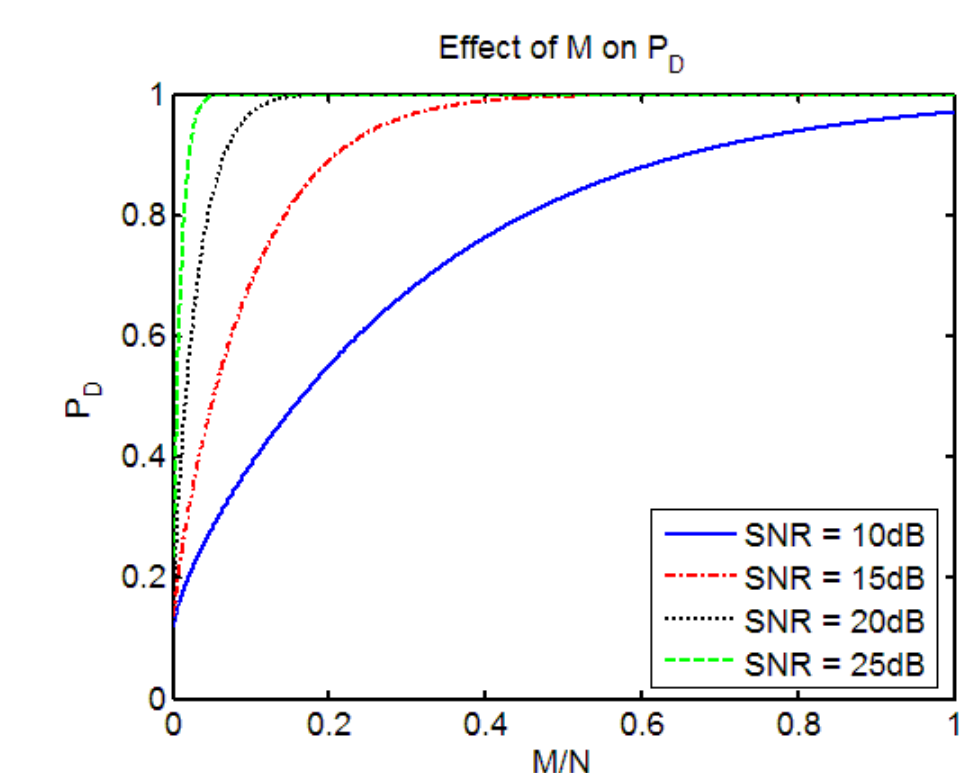
$$H_0 : y = \Phi n$$

$$H_1 : y = \Phi(s + n)$$

Neyman-Pearson optimal detector is the

compressive matched filter $t = \langle y, \Phi s \rangle$, with ROC

$$P_D(\alpha) = Q\left(Q^{-1}(\alpha) - \frac{\|\Phi s\|_2}{\sigma}\right) \approx Q\left(Q^{-1}(\alpha) - \sqrt{\frac{M}{N}} \frac{\|s\|_2}{\sigma}\right)$$

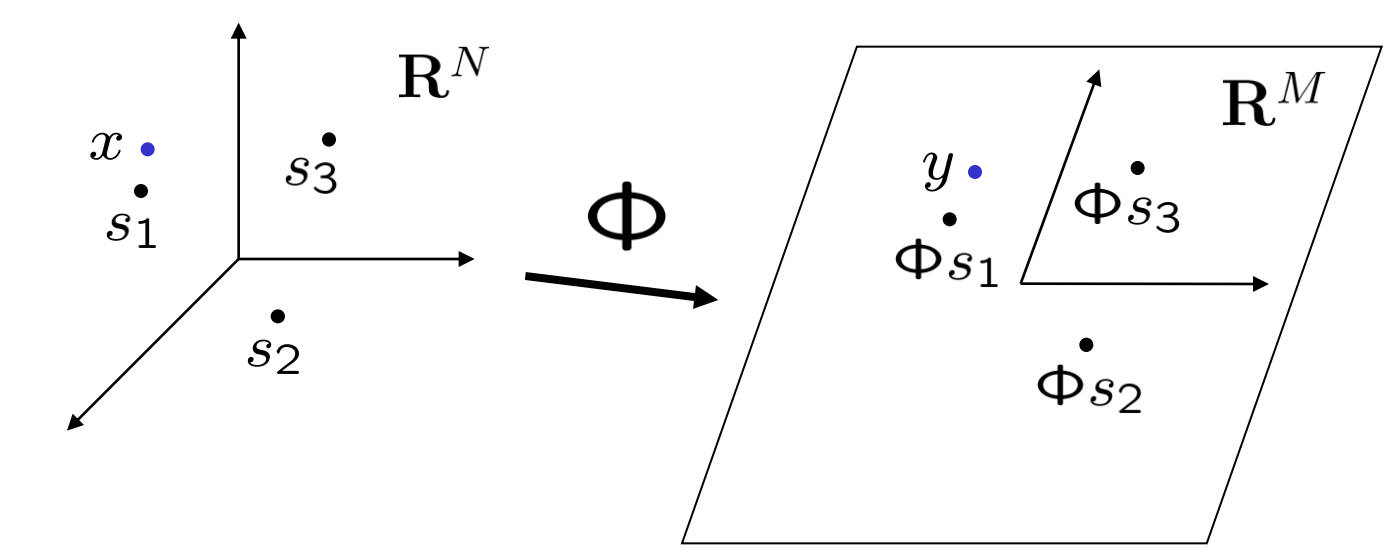


Classification

More generally, suppose we want to

distinguish between s_1, s_2, s_3, \dots

$$\left. \begin{aligned} t_1 &= \|y - \Phi s_1\|_2 \\ t_2 &= \|y - \Phi s_2\|_2 \\ t_3 &= \|y - \Phi s_3\|_2 \end{aligned} \right\} \begin{array}{l} \text{Distances preserved by} \\ \text{concentration of measure} \\ \text{(Johnson-Lindenstrauss lemma)} \end{array}$$

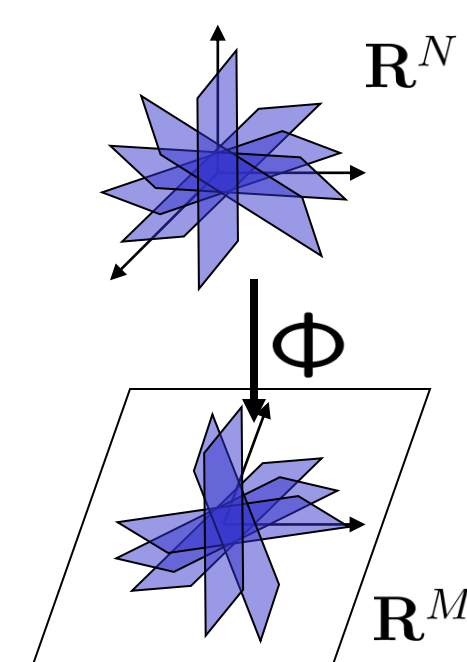


Low-Dimensional Models

Sparse Signal Models

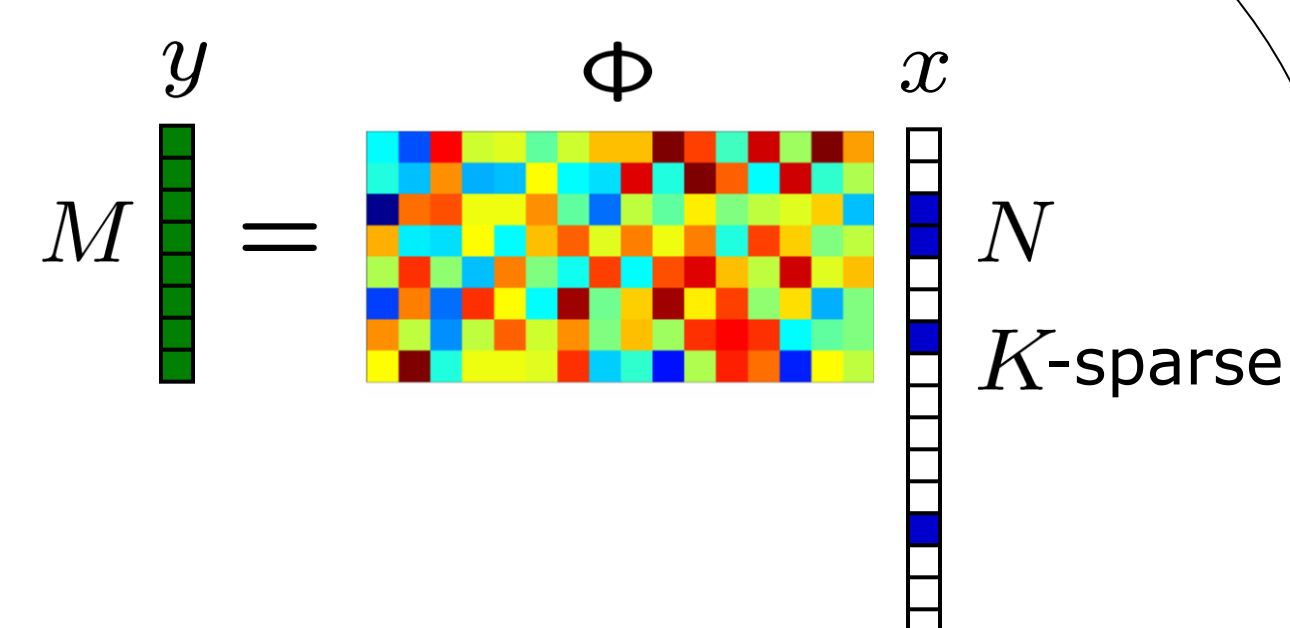
Compressed Sensing takes advantage of the low-dimensional structure of sparse signals

Concentration of measure allows embedding

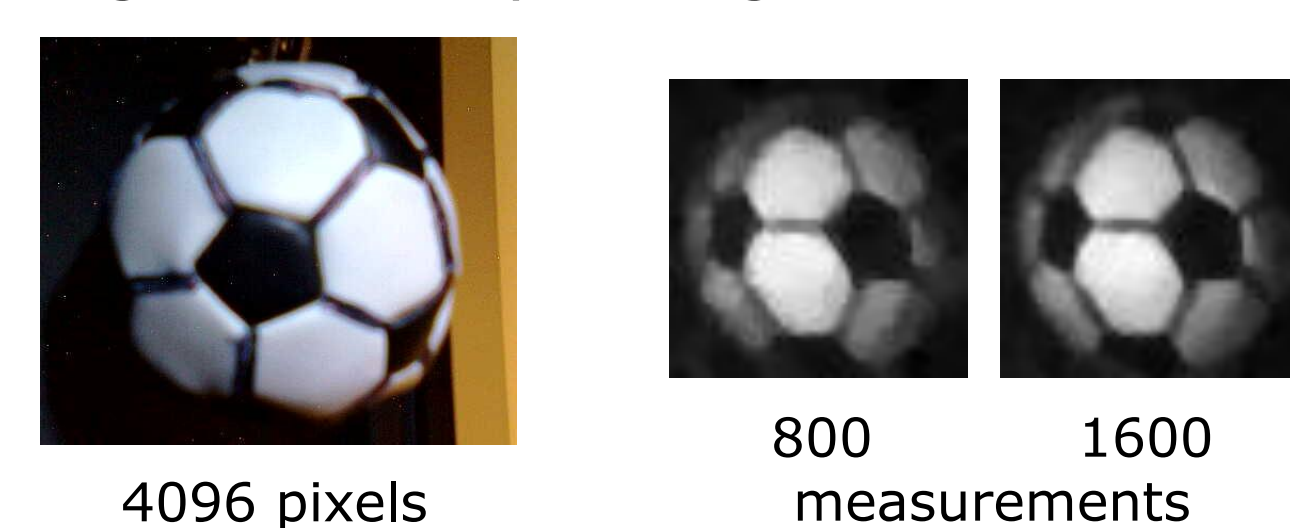


$$M = O(K \log N)$$

$$(1 - \epsilon) \leq \frac{\|\Phi x\|_2}{\|x\|_2} \leq (1 + \epsilon)$$

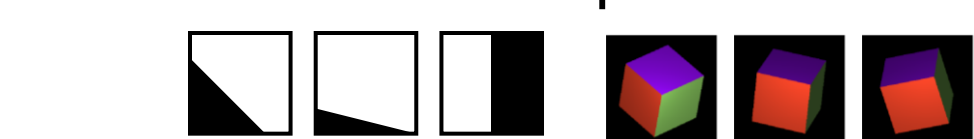


Signal recovery through ℓ_1 minimization

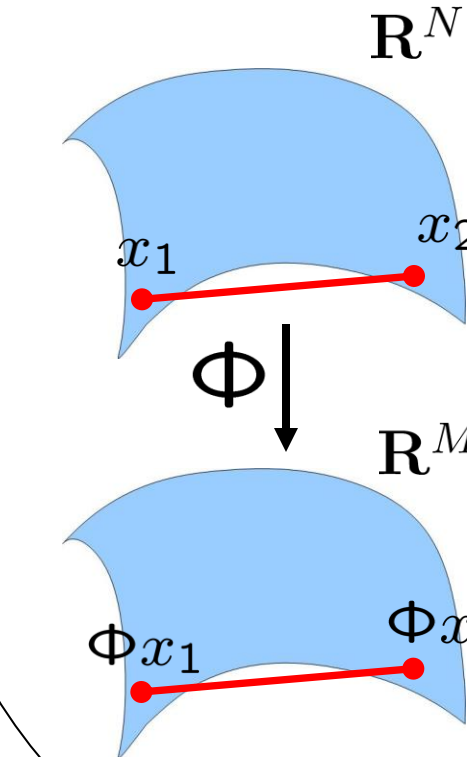


Manifold Signal Models

Low-dimensional parametric structure

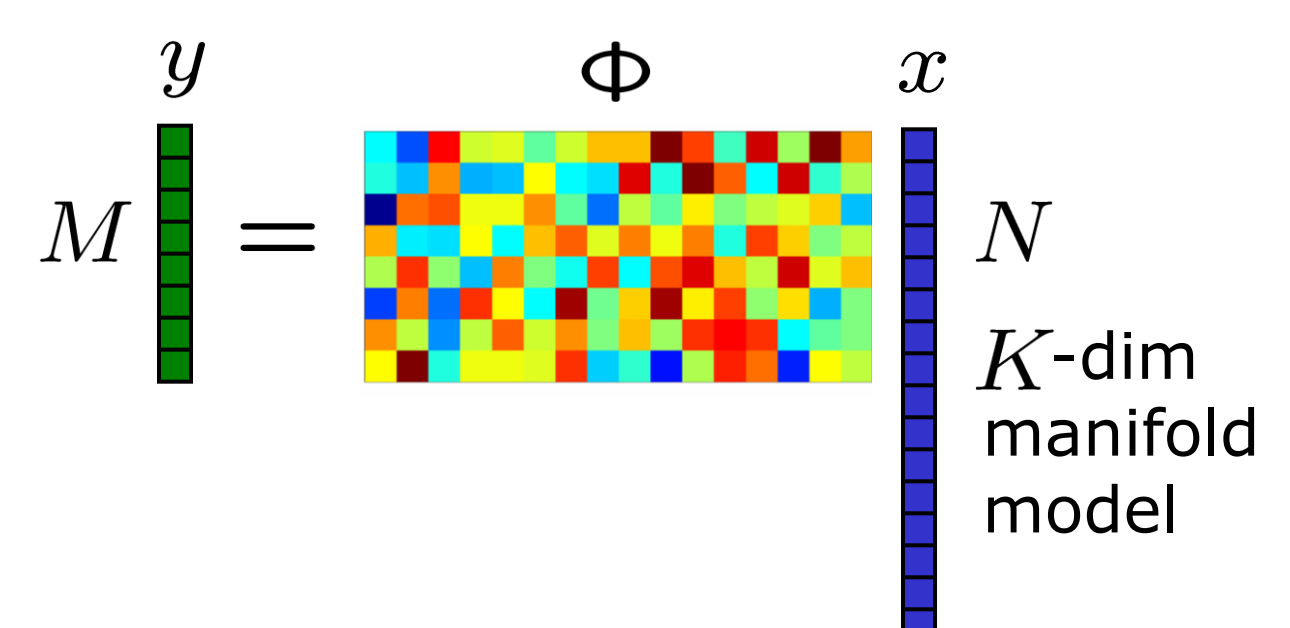


Concentration of measure



$$M = O(K \log N)$$

$$(1 - \epsilon) \leq \frac{\|\Phi x_1 - \Phi x_2\|_2}{\|x_1 - x_2\|_2} \leq (1 + \epsilon)$$



Signal recovery



Low-Complexity Inference with Low-Dimensional Models

Estimation, Detection, and Classification

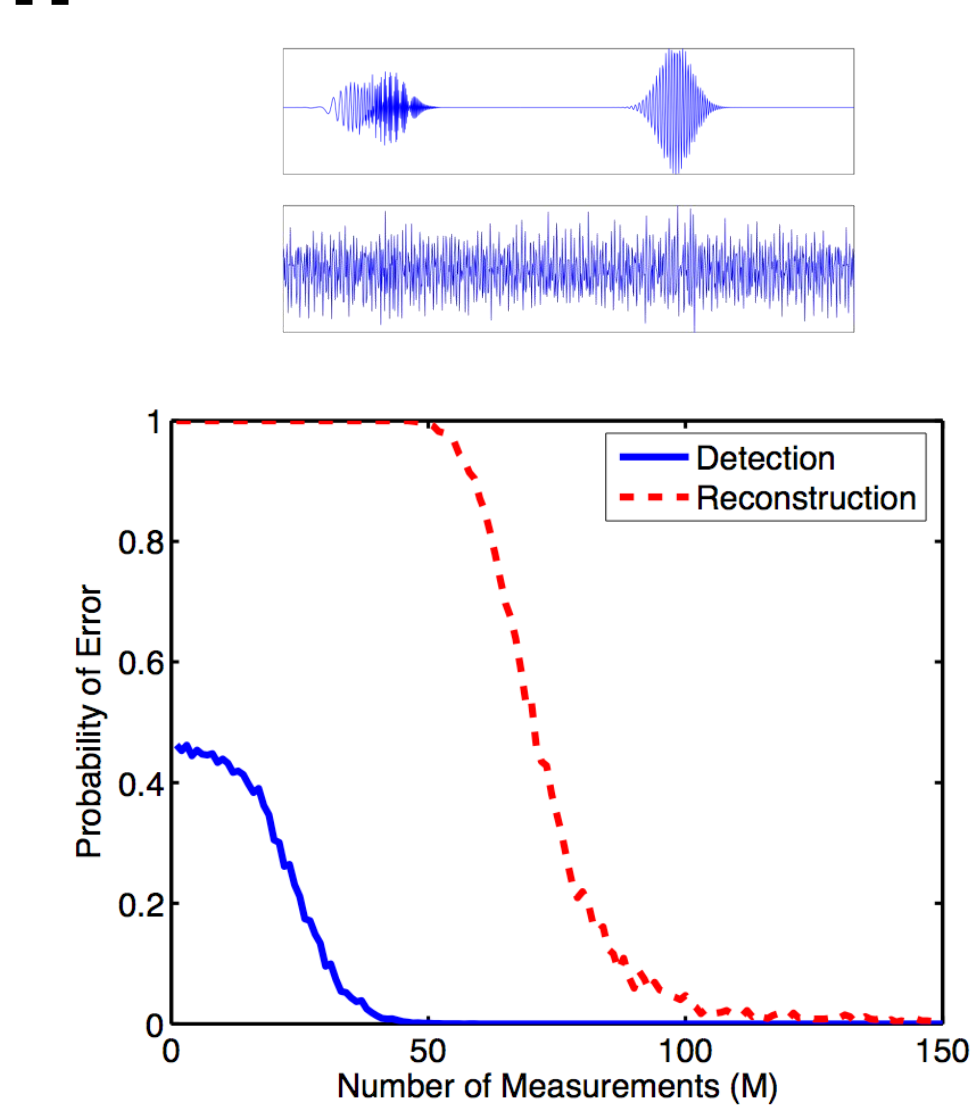
Combine low-complexity inference with sparse models

IDEA – Incoherent Estimation and Detection Algorithm

- greedy algorithm for obtaining a partial reconstruction
- estimate and cancel sparse/compressible noise
- threshold recovered coefficients

Case study: Wideband chirps in narrowband noise

- weak signal of interest in heavy, narrowband noise
- can detect using *3x fewer measurements* compared to greedy reconstruction

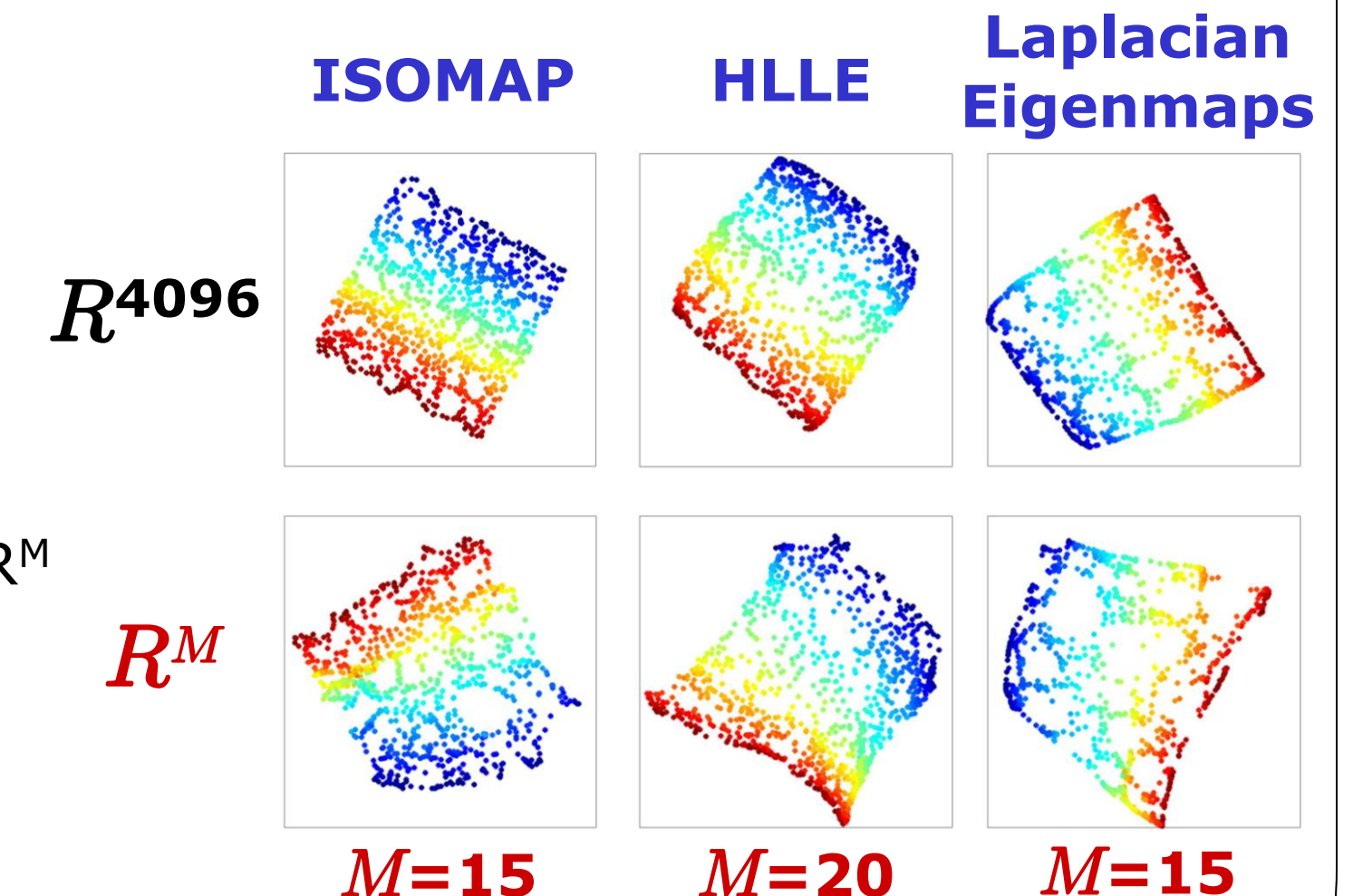
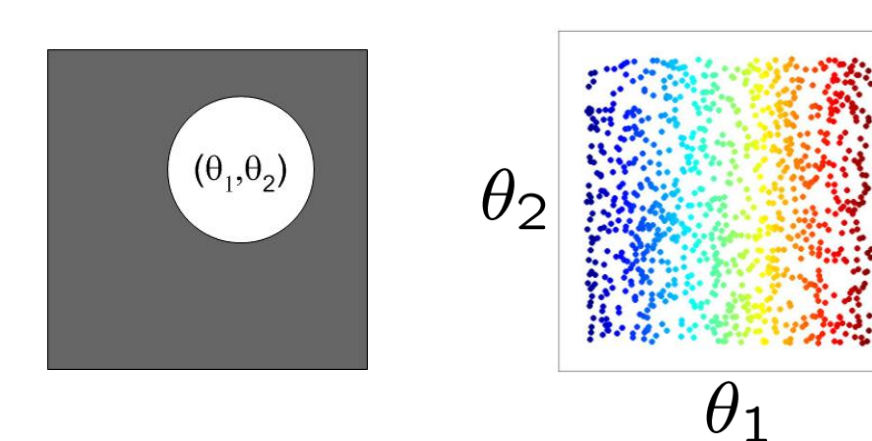


Manifold Learning

Random projections preserve key manifold properties

- distances (ambient & geodesic) between points
- dimension, volume, and topology of the manifold
- lengths and curvature of paths on the manifold

Learn these features from sampled, *projected* data in \mathbb{R}^M



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Decreasing Complexity of Signal

Decreasing Complexity of Inference