High-dimensional statistics: Some progress and challenges ahead

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University College, London Master Class: Lecture 3

Joint work with: Alekh Agarwal, Arash Amini, Po-Ling Loh, Sahand Negahban, Garvesh Raskutti, Pradeep Ravikumar, Bin Yu.

Non-parametric regression

Goal: How to predict output from covariates?

- given covariates $(x_1, x_2, x_3, \ldots, x_p)$
- output variable y
- want to predict y based on $(x_1, \ldots, x_p)$

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Different models: Ordered in terms of complexity/richness:

- linear
- non-linear but still parametric
- semi-parametric
- non-parametric

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Challenge:

How to control statistical and computational complexity for large number of predictors p?

High dimensions and sample complexity

Possible models:

- ordinary linear regression: $y = \underbrace{\sum_{j=1}^{p} \theta_j x_j}_{\langle \theta, x \rangle} + w$
- general non-parametric model: $y = f(x_1, x_2, \ldots, x_p) + w$.

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Sample complexity: How many samples n for reliable prediction?

- linear models
  - without any structure: sample size $n \asymp \underbrace{p/\epsilon^2}_{\text{linear in } p}$ necessary/sufficient

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- non-parametric models: p-dimensional, smoothness α

Curse of dimensionality: $n \asymp \underbrace{(1/\epsilon)^{2+p/\alpha}}_{\text{Exponential in } p}$

Structure in non-parametric regression

Upshot: Essential to impose structural constraints for high-dimensional non-parametric models.

Reduced dimension models:

- dimension-reducing function: $\varphi : \mathbb{R}^p \rightarrow \mathbb{R}^k$, where $k \ll p$
- lower-dimensional function: $g : \mathbb{R}^k \rightarrow \mathbb{R}$
- composite function: $f : \mathbb{R}^p \rightarrow \mathbb{R}$

$$f(x_1, x_2, \ldots, x_p) = g\big(\varphi(x_1, x_2, \ldots, x_p)\big)$$

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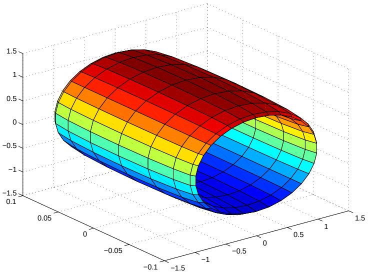
Example: Regression on k-dimensional manifold:

Form of model

$$f(x_1, x_2, \ldots, x_p) = g\big(\varphi(x_1, x_2, \ldots, x_p)\big)$$

φ is co-ordinate mapping.



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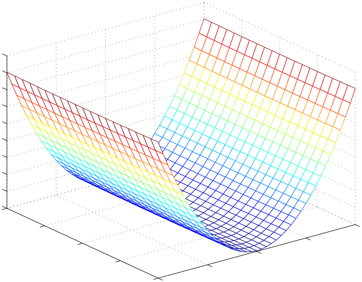
Example: Ridge functions

Form of model:

$$f(x_1, x_2, \ldots, x_p) = \sum_{j=1}^{k} g_j\big(\langle a_j,\, x\rangle\big)$$

Dimension-reducing mapping

$\varphi(x_1, \ldots, x_p) = Ax \qquad$ for some $A \in \mathbb{R}^{k \times p}$.



Remainder of lecture

1. Sparse additive models
   - formulation, applications
   - families of estimators
   - efficient implementation as SOCP
2. Statistical rates
   - Kernel complexity
   - Subset selection plus univariate function estimation
3. Minimax lower bounds
   - Statistics as channel coding
   - Metric entropy and lower bounds

Sparse additive models

- additive models $f(x_1, x_2, \ldots, x_p) = \sum_{j=1}^{p} f_j(x_j)$
  (Stone, 1985; Hastie & Tibshirani, 1990)

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- additivity with sparsity

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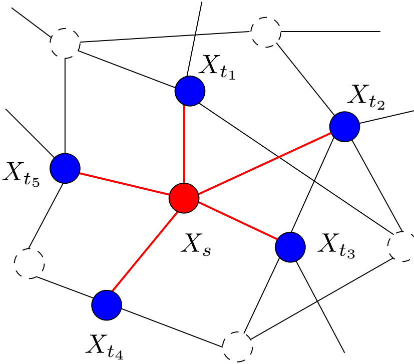
- studied by previous authors:
  - Lin & Zhang, 2006: COSSO relaxation,
  - Ravikumar et al., 2007: SPAM back-fitting procedure, consistency
  - Bach et al., 2008: multiple kernel learning (MLK), consistency in classical setting
  - Meier et al., 2007, $L^2(\mathbb{P}_n)$ regularization
  - Koltchinski & Yuan, 2008, 2010.
  - Raskutti, W. & Yu, 2009: minimax lower bounds

Application: Copula methods and graphical models

- transform $X_j \mapsto Z_j = f_j(X_j)$
- model $(Z_1, \ldots, Z_p)$ as jointly Gaussian Markov random field

$$\mathbb{P}(z_1, z_2, \ldots, z_p) \propto \exp\Big\{ \sum_{(s,t) \in E} \theta_{st} z_s z_t \Big\}.$$



- exploit Markov properties: neighborhood-based selection for learning graphs (Besag, 1974; Meinshausen & Buhlmann, 2006)
- combined with copula method: semi-parametric approach to graphical model learning (Liu, Lafferty & Wasserman, 2009)

Sparse and smooth

Noisy samples

$$y_i = f^*(x_{i1}, x_{i2}, \ldots, x_{ip}) + w_i \qquad \text{for } i = 1, 2, \ldots, n$$

of unknown function f^* with:

- sparse representation: $f^* = \sum_{j \in S} f_j^*$
- univariate functions are smooth: $f_j \in \mathcal{H}_j$

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- Disregarding computational cost:

$$\min_{|S| \leq s} \quad \min_{\substack{f = \sum\limits_{j \in S} f_j \\ f_j \in \mathcal{H}_j}} \underbrace{\frac{1}{n} \sum_{i=1}^{n} \big(y_i - f(x_i)\big)^2}_{\|y - f\|_n^2}$$

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$$\|f\|_{1,\mathcal{H}} := \sum_{j=1}^{p} \|f_j\|_{\mathcal{H}_j}$$

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- 1-$L_2(\mathbb{P}_n)$-norm as convex surrogate:

$$\|f\|_{1,n} := \sum_{j=1}^{p} \|f_j\|_{L^2(\mathbb{P}_n)}$$

where $\|f_j\|_{L^2(\mathbb{P}_n)}^2 := \frac{1}{n}\sum_{i=1}^{n} f_j^2(x_{ij})$.

A family of estimators

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Estimator:

$$\widehat{f} \in \arg \min_{f = \sum_{j=1}^{p} f_j} \Big\{ \frac{1}{n} \sum_{i=1}^{n} \big(y_i - \sum_{j=1}^{p} f_j(x_{ij}) \big)^2 + \rho_n \|f\|_{1,\mathcal{H}} + \mu_n \|f\|_{1,n} \Big\}.$$

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Two kinds of regularization:

$$\|f\|_{1,n} = \sum_{j=1}^p \|f_j\|_{L^2(\mathbb{P}_n)} = \sum_{j=1}^p \sqrt{\frac{1}{n} \sum_{i=1}^n f_j^2(x_{ij})}, \quad \text{and}$$

$$\|f\|_{1,\mathcal{H}} = \sum_{j=1}^p \|f_j\|_{\mathcal{H}_j}.$$

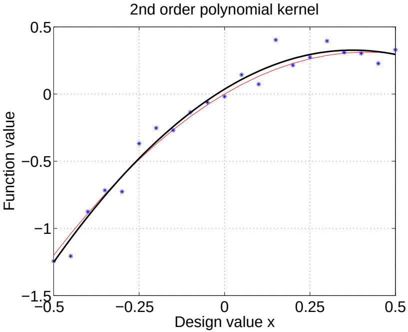
Example: Polynomial kernels

Polynomial kernel

$$\mathbb{K}(z, x) = \big(1 + \langle z,\, x\rangle\big)^d$$

Functions in span of data:

$$f(z) = \sum_{i=1}^{n} \alpha_i \big(1 + \langle z,\, x_i\rangle\big)^d$$



Example: First-order Sobolev kernel

First-order Sobolev kernel

$$\mathbb{K}(z, x) = 1 + \min\{z, x\}$$

Functions in span of data are Lipschitz:

$$f(z) = \sum_{i=1}^{n} \alpha_i \big(1 + \min\{z, x\}\big)$$

Efficient implementation by kernelization

Representer theorem: Reduces to convex program involving:

- matrix $A = (\alpha_1, \alpha_2, \ldots, \alpha_p) \in \mathbb{R}^{n \times p}$.
- empirical kernel matrices $[K_j]_{i\ell} = \mathbb{K}_j(x_{ij}, x_{\ell j})$.

(Kimeldorf & Wahba, 1971)

Original estimator and kernelized form:

$$\widehat{f} \in \arg \min_{f = \sum_{j=1}^p f_j} \Big\{ \frac{1}{n} \sum_{i=1}^n \big(y_i - \sum_{j=1}^p f_j(x_{ij}) \big)^2 | + \rho_n \sum_{j=1}^p \|f_j\|_{\mathcal{H}_j} + \mu_n \sum_{j=1}^p \|f_j\|_{L^2(\mathbb{P}_n)} \Big\}$$

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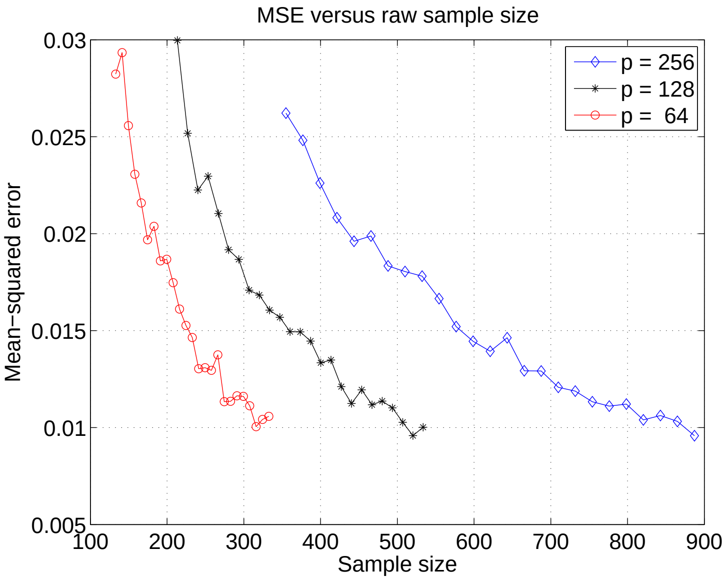
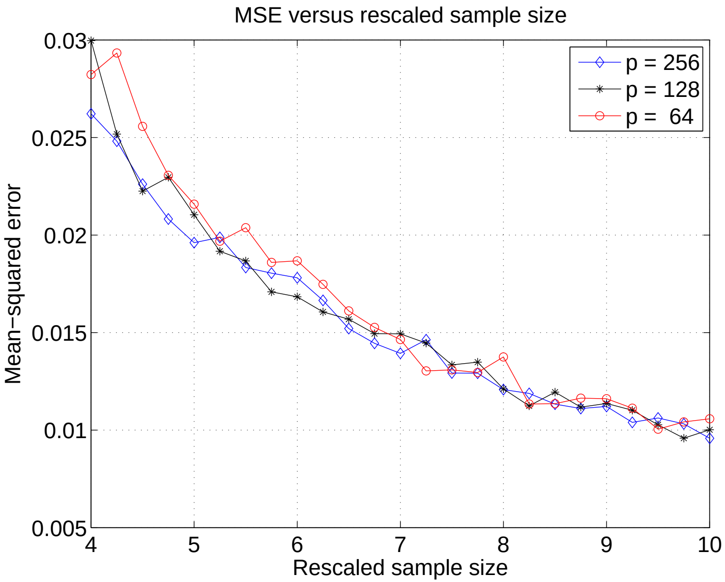
$$\widehat{A} \in \arg \min_{A \in \mathbb{R}^{n \times p}} \Big\{ \frac{1}{n} \|y - \sum_{j=1}^{p} K_j \alpha_j\|_2^2 + \rho_n \sum_{j=1}^{p} \sqrt{\alpha_j^T K_j \alpha_j} + \mu_n \sum_{j=1}^{p} \sqrt{\alpha_j^T K_j^2 \alpha_j} \Big\}.$$

Empirical results: Unrescaled



Empirical results: Apppropriately rescaled



Decay rate of kernel eigenvalues

Mercer's theorem: orthonormal basis $\{\phi_j\}$ and non-negative eigenvalues $\{\lambda_j\}$ such that

$$\mathbb{K}(z, x) = \sum_{j=1}^{\infty} \lambda_j \phi_j(z)\, \phi_j(x).$$

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Local Rademacher complexity

(Mendelson, 2002)

$$\mathcal{R}_{\mathbb{K}}(\delta) := \frac{1}{\sqrt{n}} \Big[\sum_{j=1}^{\infty} \min\left\{\lambda_j, \delta^2\right\} \Big]^{1/2}.$$

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Example: For Sobolev smoothness kernels:

- First-order (Lipschitz): $\lambda_j \asymp (1/j)^2$
- Second-order (Twice diff'ble): $\lambda_j \asymp (1/j)^4$

Achievable results

Model:

- f^* has $s \ll p$ non-zero components
- each univariate component f_j^* in same univariate Hilbert space $\mathcal{H}$ with eigenvalues $\{\lambda_j\}$
- critical univariate rate δ_n determined by solving

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Theorem (Raskutti, W. & Yu, 2010, 2012)

For appropriate choices of regularization parameters ρ_n, μ_n, we have

$$\|\widehat{f} - f^*\|^2_{L^2(\mathbb{P}_n)} \;\precsim\; \underbrace{\frac{s \log p}{n}}_{\textit{Cost of subset selection}} \;+\; \underbrace{s\,\delta_n^2}_{\textit{Cost of } s\textit{-variate estimation}}$$

with high probability.

Consequence: Kernels with exponential decay

- univariate kernel with α-exponential eigendecay eigenvalue decay

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  - $\alpha = 2$: Lipschitz functions
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Consequence: Finite-rank kernels

- a (block) univariate kernel $\mathbb{K}$ has rank m if $\lambda_j = 0$ for all $j > m$.
- many examples:
  - linear function classes in $\mathbb{R}^m$
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For any kernel with rank m, we have

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- Concurrent work: Koltchinski & Yuan, 2010:
  - analyze same estimator but under a global boundedness condition
  - rates are not minimax-optimal

Rates with global boundedness

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- similar rates claimed to be optimal

Proposition (Raskutti, W. & Yu, 2010)

Faster rates are possible under global boundedness conditions. For any Sobolev kernel with smoothness α,

$$\|\widehat{f} - f^*\|^2_{L^2(\mathbb{P}_n)} \; \precsim \; \phi(s,n) \, \frac{s}{n^{\frac{2\alpha}{2\alpha+1}}} + \frac{s \log(p/s)}{n}$$

for a function such that $\phi(s,n) = o(1)$ if $s \succsim \sqrt{n}$.

Information-theoretic lower bounds

Thus far:

- polynomial-time algorithm based on solving SOCP
- upper bounds on error that hold w.h.p.

Question:

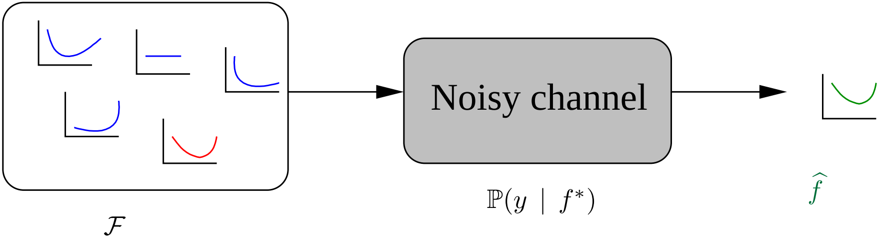
But are these "good" results?

Statistical minimax: For a function class $\mathcal{F}$, define the minimax error:

$$\mathfrak{M}_n(\mathcal{F}_{s,p,\alpha}) := \inf_{\widehat{f}} \sup_{f^* \in \mathcal{F}_{s,p,\alpha}} \|\widehat{f} - f^*\|_2^2.$$

Lower bounds behavior of any algorithm over class $\mathcal{F}$.

Function estimation as channel coding



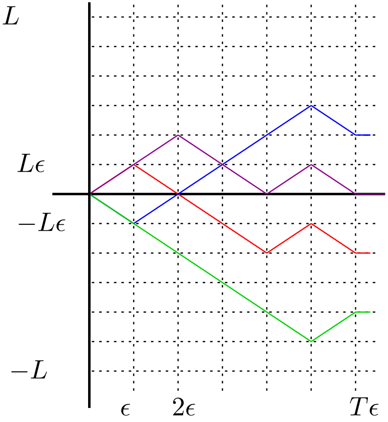
1. Nature chooses a function f^* from a class $\mathcal{F}$.

2. User makes n observations of f^* from a noisy channel.

3. Function estimation as decoding: return estimate $\widehat{f}$ based on samples $\{(y_i, x_i)\}_{i=1}^n$.

(Hasminskii, 1978, Birge, 1981, Yang & Barron, 1999)

Complexity of function classes



- complexity measured by packing number (Kolmogorov & Tikhomirov, 1960)
- ϵ-packing set: functions $\{f^1, f^2, \ldots, f^M\}$ such that $\|f^j - f^k\| > \epsilon$ for all $j \neq k$

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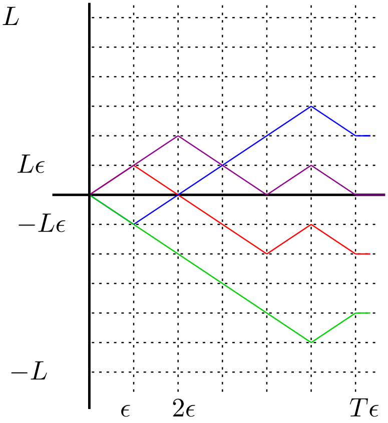

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- for Lipschitz functions in 1-dimension:

$$M(\epsilon) \asymp 2^{(L/\epsilon)}.$$

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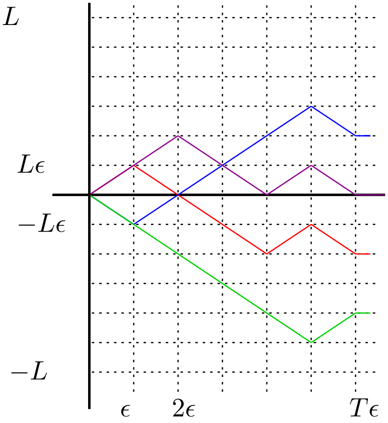

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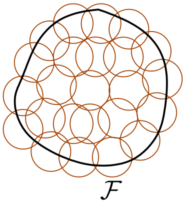
- for Lipschitz functions in p-dimensions

$$M(\epsilon) \asymp 2^{(L/\epsilon)^p}.$$

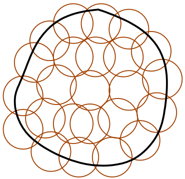
Metric entropy classes



Covering number

$N(\delta; \mathcal{F}) =$ smallest # δ-balls needed to cover $\mathcal{F}$

Metric entropy classes



$\mathcal{F}$

Covering number

$N(\delta; \mathcal{F})$ = smallest # δ-balls needed to cover $\mathcal{F}$

---

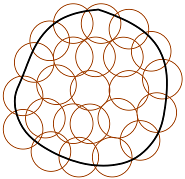
1. Logarithmic metric entropy

$$\log N(\delta; \mathcal{F}) \asymp m \log(1/\delta)$$

Examples:

- parametric classes
- finite-rank kernels
- any function class with finite VC dimension

Metric entropy classes



Covering number

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1. Polynomial metric entropy:

$$\log N(\delta; \mathcal{F}) \asymp \left(\frac{1}{\delta}\right)^{\frac{1}{\alpha}}$$

Examples:

- various smoothness classes
- Sobolev classes

Lower bounds on minimax risk

Theorem (Raskutti, W. & Yu, 2010)

Under the same conditions, there is a constant $c_0 > 0$ such that:

1. *For function class $\mathcal{F}$ with m-logarithmic metric entropy:*

$$\mathbb{P}\Big[\mathfrak{M}_n(\mathcal{F}_{s,p,\alpha}) \geq c_0 \Big\{ \underbrace{\frac{s \log p/s}{n}}_{\textit{subset sel.}} + \underbrace{s\left(\frac{m}{n}\right)}_{\textit{s-var. est.}} \Big\}\Big] \geq 1/2.$$

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2. *For function class $\mathcal{F}$ with α-polynomial metric entropy:*

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Summary

- structure is essential for high-dimensional non-parametric models
- sparse and smooth additive models:
  - convex relaxation based on a composite regularizer
  - attains minimax-optimal rates for kernel classes:
    - cost of subset selection: $s\frac{\log p/s}{n}$
    - cost of s-variate function estimation: $s\delta_n^2$

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Related paper:

Raskutti, W., & Yu (2012). Minimax-optimal rates for sparse additive models over kernel classes. *Journal of Machine Learning Research*, March 2012.