Estimating Manifolds Supplementary Materials

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Proof Sketch: Lower Bounds

The lower bound is established with Le Cam's Lemma.

Suppose Y_1, \ldots, Y_n drawn IID from \mathcal{Q} , an estimator $\widehat{\theta} \equiv \widehat{\theta}(Y_1, \ldots, Y_n)$, and a (weak, semi-) metric *ρ*.

Then for any pair $Q_0, Q_1 \in \mathcal{Q}$

 $\sup_{\Omega\in\Omega} \mathbb{E}_{Q^n}\rho(\widehat{\theta},\theta(Q)) \geq C\rho(\theta(Q_0),\theta(Q_1))(1-\mathsf{TV}(Q_0,Q_1))^{2n},$ Q∈Q

where

$$
TV(Q_0(A), Q_1(A)) = \sup_A |Q_0(A) - Q_1(A)| = \frac{1}{2} \int |q_0 - q_1|.
$$

Hence, for each given Hausdorff distance, we want to choose a least favorable pair of manifolds whose distributions are as hard to distinguish as possible.

Perpendicular Noise: Sketch of Lower Bound

Construct M_0 and M_1 such that:

- Mⁱ ∈ M*^κ*
- Haus $(M_1, M_0) = \gamma$
- TV $\equiv \int |q_1 q_0| = O(\gamma^{(d+2)/2})$, which is minimum possible.

Apply Le Cam's Lemma: For any \widehat{M} :

$$
\sup_{Q \in \mathcal{Q}} \mathbb{E}_{Q^n} \text{Haus}(M, \widehat{M}) \ge \text{Haus}(M_1, M_0) \times (1 - \text{TV})^{2n}
$$

$$
= \gamma (1 - c \gamma^{(d+2)/2})^{2n}.
$$

Setting $\gamma = n^{-2/(d+2)}$ yields the result.

Least Favorable Pair M_0 and M_1 : M_0 = plane and M_1 = "flying saucer".

Perpendicular Noise: Sketch of Upper Bound

Construct an "estimator" that achieves the bound:

- **1** Split the data into two halves.
- **2** Using the first half, construct a pilot esimator. This is a (sieve) maximum likelihood estimator.
- **3** Cover the pilot estimator with thin, long, slabs.
- **4** Using the second half of the data, fit local linear estimators M_j in slab j
- $\mathbf{M} = \bigcup_j M_j.$

The details are messy and the estimator is not practical, but it suffices for establishing the bound.

Clutter Model

Suppose

$$
Y_1,\ldots,Y_n\sim Q\equiv (1-\pi)U+\pi G
$$

where $0<\pi\leq 1,\;U$ is uniform on the compact set $\mathcal{K}\subset\mathbb{R}^D$, and G supported on M as before.

Then,

$$
\inf_{\widehat{M}} \sup_{Q \in \mathcal{Q}} \mathbb{E}_{Q^n} \, \text{Haus}(\widehat{M}, M) \asymp^* C \left(\frac{1}{n\pi} \right)^{\frac{2}{d}}.
$$

(The \times^* means I am hiding log factors.)

Lower bound uses the same least favorable pair.

Clutter Model: Upper Bound

Let

- $\epsilon_n = (\log n/n)^{2/d}$.
- Q_n be the empirical measure.
- $S_M(y)$ denotes a $\epsilon^{d/2} \times \epsilon^{D-d}$ slab:

Define

$$
s(M) = \inf_{y \in M} \widehat{Q}_n[S_M(y)] \text{ and } \widehat{M}_n = \operatorname*{argmax}_{M} s(M).
$$

Additive Model

 $X_1, X_2, \ldots, X_n \sim G$ where support(G) = M, and $Y_i = X_i + Z_i, \qquad i = 1, \dots, n,$

where $Z_i \sim \Phi =$ Gaussian.

This is analogous to an errors-in-variables problem, except:

- **1** We want to estimate the support of G not G itself.
- **2** G is singular.
- **3** The underlying object is a manifold not a function.

Additive Model

For technical reasons, we allow the manifolds to be noncompact. Define a truncated loss function,

$$
L(M,\widehat{M})=H(M\cap\mathcal{K},\widehat{M}\cap\mathcal{K}).
$$

Then,

$$
\inf_{\widehat{M}} \sup_{Q \in \mathcal{Q}} \mathbb{E}_Q[L(M, \widehat{M})] \geq \frac{C}{\log n}.
$$

Rate is similar to deconvolution but the proof is somewhat different (since Q_0 and Q_1 have different supports). Least favorable pair:

Additive Model: Upper Bound

Let \hat{g} be a deconvolution density estimator (though G has no density), and let $M = {\hat{g} > \lambda}$.

Fix any $0 < \delta < 1/2$.

$$
\inf_{\widehat{M}} \sup_{Q \in \mathcal{Q}} \mathbb{E}_{Q}[L(M, \widehat{M})] \leq C \left(\frac{1}{\log n} \right)^{\frac{1-\delta}{2}}.
$$

In some special cases, we can achieve $\frac{1}{\log n}$ but, in general, not.