Understanding Nonparametric Multimodal Regression via Kernel Density Estimation

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Motivation

- Why modal regression?
- Conventional regression methods may fail when:
  - conditional distribution is heavy-tailed;
  - conditional distribution is multi-modal.
- Why nonparametric modal regression?
- Taking a nonparametric model allows for more flexibility unlike a (restrictive) parametric model: $\mathtt{Mode}(Y|X = x) = \beta_0 + \beta^T x$ (Sager and Thisted (1982)).

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Motivating Examples

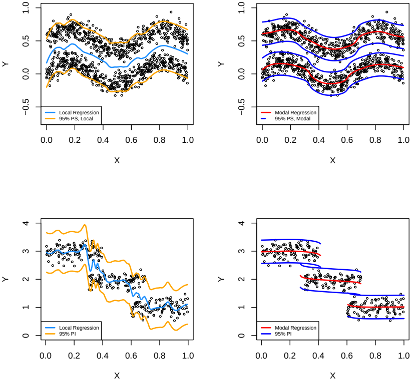

Figure: We show local regression estimate and its associated 95% prediction bands alongside the modal regression and its 95% prediction bands for two different simulated data.

Definitions

- We define operators:
  $\texttt{UniMode} = \arg\max_z f(z)$, $\texttt{MultiMode} = \{z : f'(z) = 0, f''(z) < 0\}$.

Definition (Uni-modal function)

$m(x) = \texttt{UniMode}(Y|X = x) = \arg\max_y p(y|x)$.

Definition (Multi-modal function)

$M(x) = \texttt{MultiMode}(Y|X = x) = \{y : \frac{\partial}{\partial y} p(y|x) = 0, \frac{\partial^2}{\partial y^2} p(y|x) < 0\}$.

- Equivalently, we can write,

$$m(x) = \arg\max_y p(x, y), \quad M(x) = \{y : \frac{\partial}{\partial y} p(x, y) = 0, \frac{\partial^2}{\partial y^2} p(x, y) < 0\}. \tag{1}$$

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Uni-modal vs. Multi-modal Regression

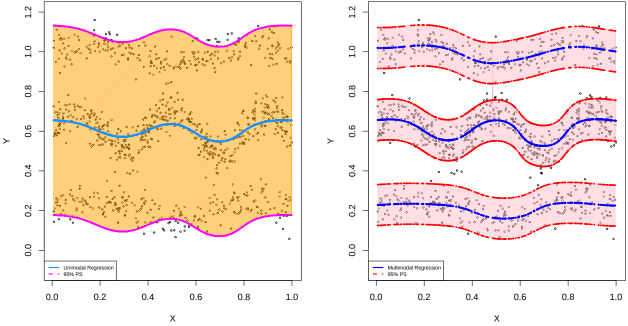

Figure: Uni-modal regression and multi-modal regression along with their corresponding 95% prediction sets on a simulated data with three components.

Modal Regression Estimators

- Our estimator is plug-in from the KDE:

$$\hat{M}_n(x) = \{y : \frac{\partial}{\partial y}\hat{p}_n(x,y) = 0,\ \frac{\partial^2}{\partial y^2}\hat{p}_n(x,y) < 0\}, \tag{2}$$

where

$$\hat{p}_n(x,y) = \frac{1}{nh^{d+1}}\sum_{i=1}^{n} K\left(\frac{||x-X_i||}{h}\right)K\left(\frac{y-Y_i}{h}\right). \tag{3}$$

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The Mean-shift Algorithm

Input: Data samples $\mathscr{D} = \{(X_1, Y_1), ..., (X_n, Y_n)\}$, bandwidth h.
(The kernel K is assumed to be Gaussian.)

1. Initialize mesh points $\mathscr{M} \subset R^{d+1}$ (a common choice is $\mathscr{M} = \mathscr{D}$, the data samples).
2. For each $(x, y) \in \mathscr{M}$, fix x, and update y using the following iterations until convergence:

$$y \longleftarrow \frac{\sum_{i=1}^{n} Y_i K\left(\frac{||x-X_i||}{h}\right) K\left(\frac{y-Y_i}{h}\right)}{\sum_{i=1}^{n} K\left(\frac{||x-X_i||}{h}\right) K\left(\frac{y-Y_i}{h}\right)} \tag{4}$$

Output: The set $\mathscr{M}^{\infty}$, containing the points (x, y^{∞}), where x is a predictor value as fixed in $\mathscr{M}$, and y^{∞} is the corresponding limit of the mean-shift iterations.

Algorithm 1: Partial mean-shift algorithm

Modal Manifolds Collection: Definitions

- We define a *modal manifold collection* over all inputs x as:

$$\mathbb{S} = \{(x, y) : x \in D, y \in M(x)\}.$$

- We assume $\mathbb{S}$ can be factorized as:

$$\mathbb{S} = \{(x, y) : x \in D, y \in M(x)\} = \mathbb{S}_1 \cup \cdots \cup \mathbb{S}_K, \tag{5}$$

where each $\mathbb{S}_j$, $j = 1, 2, \ldots, K$ is a connected manifold defined as follows:

$$\mathbb{S}_j = \{(x, m_j(x)) : x \in A_j\}, \tag{6}$$

for some function $m_j(x)$ and open set A_j.

- As a convention, $m_j(x) = \phi$ if $x \notin A_j$.
- This effectively allows us to write

$$M(x) = \{m_1(x), \ldots, m_K(x)\}.$$

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Modal Manifold Collection: An example

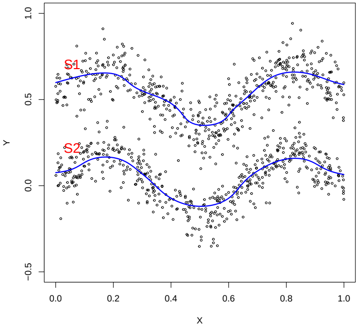

Figure: S1 and S2 represent modal manifolds.

Derivative of Modal Functions

Lemma (Derivative of modal functions)

Assume that p is twice differentiable, and let $\mathbb{S} = \{(x,y) : x \in D, y \in M(x)\}$ be the modal manifold collection. Assume that $\mathbb{S}$ factorizes according to (5), (6). Then, when $x \in A_j$,

$$\nabla m_j(x) = -\frac{p_{yx}(x, m_j(x))}{p_{yy}(x, m_j(x))}, \tag{7}$$

where $p_{yx} = \nabla_x \frac{\partial}{\partial y} p(x,y)$ is the gradient over x of $p_y(x,y)$.

- **Interpretation:** When p is smooth, each modal manifold is also smooth.

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Hausdorff Distance

- To characterize smoothness of $M(x)$, we require a notion of distance over sets: *Hausdorff Distance*.

Definition (Hausdorff Distance)

Let us consider a metric space (M, d) and suppose X and Y be two non-empty subsets of the metric space. Then the Hausdroff distance between X and Y is defined by,

$$d_H(X,Y) = \max\{\sup_{x\in X} d(x,Y), \sup_{y\in Y} d(X,y)\},$$

where $d(a,B)$ is the distance from a point a to the set B, $d(a,B) = \inf_{b\in B} d(a,b)$.

- Equivalently, we can define the Hausdorff distance as:

$$\texttt{Haus}(A,B) = \inf\{r : A \subseteq B \oplus r, B \subseteq A \oplus r\},$$

where $A \oplus r = \{x : d(x,A) \leq r\}$ with $d(x,A) = \inf_{y\in A} ||x-y||$

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Derivative of Modal Manifold Collection

Theorem (Smoothness of Modal Manifold Collection)

Assume the conditions of Lemma (3). Assume furthermore all partial derivatives of p are bounded by C, and there exists $\lambda_2 > 0$ such that $p_{yy}(x,y) < -\lambda_2$ for all $y \in M(x)$ and $x \in D$. Then

$$\lim_{|\varepsilon|\longrightarrow 0} \frac{\mathtt{Haus}(M(x), M(x+\varepsilon))}{|\varepsilon|} \leq \max_{j=1,\ldots,K} ||m_j'(x)|| \leq \frac{C}{\lambda_2} < \infty. \tag{8}$$

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Error Measurements

We consider the following losses to measure the error:

- **Pointwise Error:**

$$\Delta_n(x) = \mathtt{Haus}\{\hat{M}_n(x), M(x)\},$$

where $\mathtt{Haus}$(A,B) Hausdroff distance between the sets A and B.

- **Uniform Error:**

$$\Delta_n = \sup_{x\in D} \Delta_n(x).$$

- **Mean Integrated Squared Error (MISE):**

$$MISE(\hat{M}_n) = \mathbb{E}\left(\int_{x\in D} \Delta_n^2(x)dx\right).$$

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Assumptions on Joint Density

Assumption (A1)

The joint density $p \in BC^4(C_p)$, for some $C_p > 0$.

Assumption (A2)

The collection of modal manifolds can $\mathbb{S}$ can be factorized into $\mathbb{S} = \mathbb{S}_1 \cup \mathbb{S}_2 \cup \ldots \cup \mathbb{S}_K$, where $\mathbb{S}_j$ is a connected curve that follows a parametrization $\mathbb{S}_j = \{(x, m_j(x)) : x \in A_j\}$ for some $m_j(x)$ and $A_1, A_2, \ldots, A_K$ form an open cover for the support D of X.

Assumption (A3)

There exists $\lambda_2 > 0$ such that for any $(x, y) \in D \times K$ with $p_y(x, y) = 0$, $|p_{yy}(x, y)| > \lambda_2$.

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Assumptions on Kernel Function

Assumption (K1)

The Kernel function $K \in BC^2(C_K)$ and satisfies for $\alpha = 0, 1, 2$,

$$\int_R (K^{(\alpha)})^2(z)dz < \infty \qquad \int_R z^2(K^{(\alpha)})(z)dz < \infty.$$

Assumption (K2)

The collection $\mathscr{K}$ is a VC-type class, i.e. there exists $A, v > 0$ such that for $0 < \varepsilon < 1$,

$$\sup_Q N(\mathscr{K}, L_2(Q), C_K\varepsilon) \leq \frac{A^v}{\varepsilon^v},$$

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Few Notations

- Before proceeding further, let us define the following quantities:

$$\|\hat{p}_n - p\|_\infty^0 = \sup_{x,y} \|\hat{p}(x,y) - p(x,y)\|.$$
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Pointwise Rate

Theorem (Pointwise Error Rate)

Assuming (A1-3) and (K1-2), we define the stochastic process $A_n(x)$ as,

$$A_n(x) = \begin{cases} \frac{1}{\Delta_n(x)} \left|\Delta_n(x) - \max_{z \in M(x)} \{ |p_{yy}^{-1}(x,z)| \, |\hat{p}_{y,n}(x,z)| \} \right|, & \text{if } \Delta_n(x) > 0 \\ 0, & \text{if } \Delta_n(x) = 0. \end{cases}$$

Then for sufficiently small $\|\hat{p}_n - p\|^*_{\infty,2}$, we will have

$$\sup_{x \in D}(A_n(x)) = O_p(\|\hat{p}_n - p\|^*_{\infty,2}).$$

- **Interpretation:** Under sufficient regularity conditions, $\Delta_n(x)$ can be approximated $\max_{z \in M(x)} \{ |p_{yy}^{-1}(x,z)| \, |\hat{p}_{y,n}(x,z)| \}$.

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Moreover, at any fixed $x \in D$, when $\frac{nh^{d+5}}{\log n} \to \infty$ and $h \to 0$ we have,

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Assuming (A1-3) and (K1-2), as $\frac{nh^{d+5}}{\log n} \to \infty$ *and* $h \to 0$,

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Ideal Confidence Sets

- In an ideal setting, following the estimation of $M_n(x)$, we could define confidence set at x by:

$$\hat{C}_n^0(x) = \widehat{M}_n(x) \oplus \delta_{n,1-\alpha}(x),$$

where
$$\mathbb{P}(\Delta_n(x) > \delta_{n,1-\alpha}(x)) = \alpha.$$

- We have, by construction, $\mathbb{P}(M(x) \in \hat{C}_n^0(x)) = 1 - \alpha$.

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Modified setup with Bootstrap sample

- Considering Bootstrap samples $(X_1^*, Y_1^*), \ldots, (X_n^*, Y_n^*)$, we define error metric based on estimated regression mode $\widehat{M}_n^*(x)$:

$$\hat{\Delta}_n^*(x) = \mathtt{Haus}(\widehat{M}_n^*(x), \widehat{M}_n(x)).$$

- Repeating bootstrap sampling B times to get $\hat{\Delta}_{1,n}^*, \ldots, \hat{\Delta}_{B,n}^*$, we get $\hat{\delta}_{n,1-\alpha}(x)$ as the solution to the equation:

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Few Definitions

- We consider the estimation problem of regression modes of smoothed joint density $\tilde{p}(x,y) = \mathbb{E}(\hat{p}_n(x,y))$, since we obtain faster convergence rate.
- Similarly let $\tilde{M}(x) = \mathbb{E}(\widehat{M}_n(x))$ be smoothed regression modes at $x \in D$.
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Theorem (Asymptotic Theory)

Under regularity conditions,

- $\sqrt{nh^{d+3}}\tilde{\Delta}_n \approx \sup_{f\in\mathscr{F}}\{|G_n(f)|\} \approx \sup_{f\in\mathscr{F}}\{\mathbb{B}(f)\}$.
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$$\left|\sqrt{nh^{d+3}}\tilde{\Delta}_n - \mathbb{B}\right| = O_{\mathbb{P}}\left(\left(\frac{\log^4 n}{nh^{d+3}}\right)^{1/8}\right).$$

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We use bootstrap to approximate Δ_n. We define another metric $\hat{\Delta}_n^* = \sup_{x \in D} \mathtt{Haus}(\widehat{M}_n^*, \widehat{M}_n(x))$.

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- **Interpretation** This theorem brings forth an equivalence in limiting distribution of $\hat{\Delta}_n^*$ and $\tilde{\Delta}_n$. Infact, The rate of convergence in distribution is $O\left(\left(\frac{\log^4 n}{nh^{d+3}}\right)^{1/8}\right)$.

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Corollary (Uniform confidence sets)

Assume (A1-3) and (K1-2). Then as $\frac{nh^6}{\log n} \to \infty$ *and* $h \to 0$,

$$\mathbb{P}\left(\tilde{M}(x) \subseteq \hat{M}_n(x) \oplus \hat{\delta}_{n,1-\alpha},\ \forall x \in D\right) = 1 - \alpha + O\left(\left(\frac{\log^4 n}{nh^{d+3}}\right)^{1/8}\right).$$

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- We define:

$$\varepsilon_{1-\alpha}(x) = \inf\{\varepsilon \geq 0 : \mathbb{P}(d(Y, M(x)) > \varepsilon \mid X = x) \leq \alpha\}.$$

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Bandwidth Selection

- We can choose the bandwidth of the KDE by minimizing the size of the prediction set.
- Choose

$$h^* = \arg\min_{h \geq 0} \mathtt{Vol}(\hat{\mathscr{P}}_{1-\alpha,h}),$$

where $\hat{\mathscr{P}}_{1-\alpha,h}$ is the estimated uniform prediction set.

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- We can choose the bandwidth of the KDE by minimizing the size of the prediction set.
- Choose

$$h^* = \arg\min_{h \geq 0} \mathtt{Vol}(\hat{\mathscr{P}}_{1-\alpha,h}),$$

where $\hat{\mathscr{P}}_{1-\alpha,h}$ is the estimated uniform prediction set.

Bandwidth Selection: Example

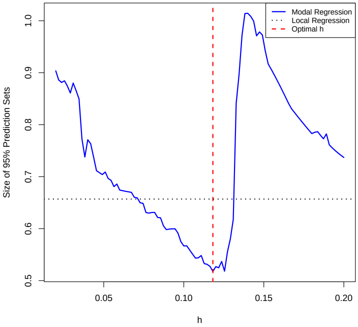

Figure: Bandwidth selection based on size of prediction sets.

Final Remarks

- We reviewed a nonparametric method for modal regression estimation, based on a KDE of a joint sample of data points $(X_1, Y_1), \dots, (X_n, Y_n)$.
- We studied some of the geometry underlying the modal regression set, and described techniques for confidence set estimation, prediction set estimation, and bandwidth selection for the underlying KDE.
- The main message is that nonparametric modal regression offers a relatively simple and usable tool to capture conditional structure missed by conventional regression methods.
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