

The Bouligand Influence Function and its Application for Support Vector Machines

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Notation

Assumptions:

- $X \subseteq \mathbb{R}^d, Y \subseteq \mathbb{R}, X \neq \emptyset, Y \neq \emptyset$
- $D = ((x_1, y_1), \dots, (x_n, y_n)), 1 \leq i \leq n$
- (X_i, Y_i) i.i.d. $\sim P \in \mathcal{M}_1, P$ (totally) unknown

Aim:

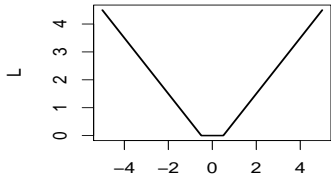
- $f(x_i) =$ quantity of interest of $P_{Y_i|X_i=x_i}$

Assumption:

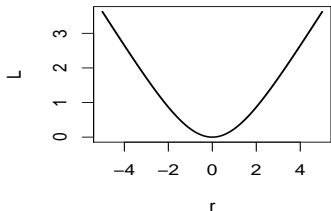
- Loss function: $L : Y \times \mathbb{R} \rightarrow [0, \infty), L(y_i, f(x_i)),$ convex

Lipschitz loss functions for regression

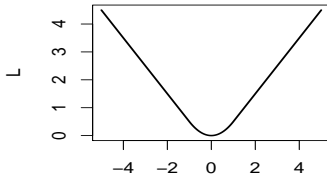
eps-insensitive, eps=0.5



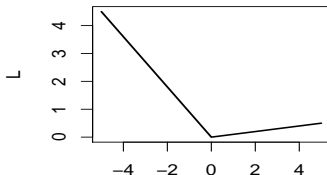
Logistic



Huber, c=1



Pinball, tau=0.10



Kernel methods

- **Kernel:** $k : X \times X \rightarrow \mathbb{R}$, if \exists Hilbert space \mathcal{H} and $\Phi : X \rightarrow \mathcal{H}$ such that

$$k(x, x') = \langle \Phi(x), \Phi(x') \rangle, \quad \forall x, x' \in X$$

Reproducing Kernel Hilbert Space (RKHS)

\mathcal{H} a Hilbert space of functions $f : X \rightarrow \mathbb{R}$. A reproducing kernel for \mathcal{H} is a kernel k with

$$f(x) = \langle f, k(x, \cdot) \rangle \quad \forall f \in \mathcal{H}, \forall x \in X.$$

- **Canonical feature map:** $\Phi(x) = k(x, \cdot)$, $x \in X$
- $k \Leftrightarrow$ RKHS unique
- **Bounded:** $\|k\|_{\infty} := \sqrt{\sup_{x \in X} k(x, x)} < \infty$
- **GRBF:** $k(x, x') = e^{-\gamma \|x - x'\|_2^2}$, $\gamma > 0$

Support Vector Machines (SVMs)

Definition

Kernel Based Regression (KBR) operator

$$S(P) = f_{P,\lambda} = \arg \min_{f \in \mathcal{H}} \mathbb{E}_P L(Y_i, f(X_i)) + \lambda \|f\|_{\mathcal{H}}^2,$$

where $P \in \mathcal{M}_1$, \mathcal{H} is a RKHS and $\lambda > 0$.

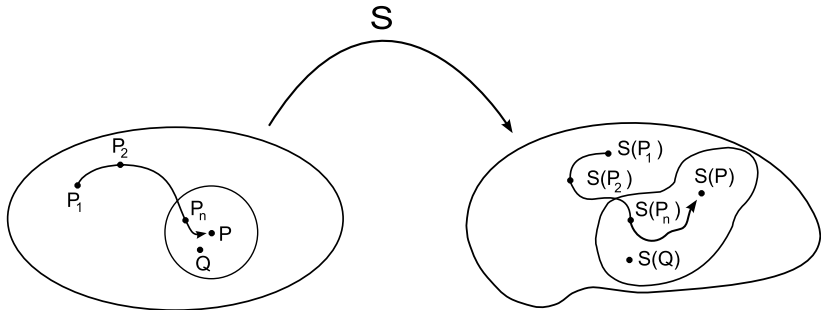
Kernel Based Regression estimator

$$S(P_n) = \arg \min_{f \in \mathcal{H}} \frac{1}{n} \sum_{i=1}^n L(Y_i, f(X_i)) + \lambda \|f\|_{\mathcal{H}}^2,$$

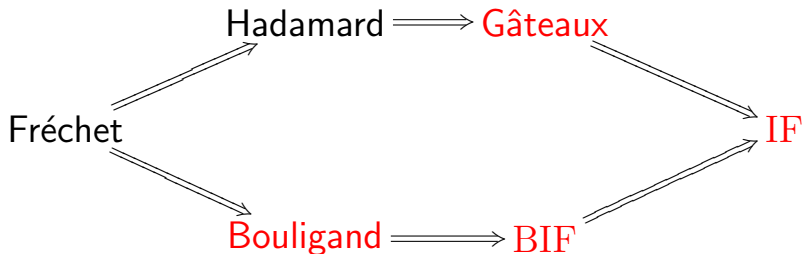
where $P_n := \frac{1}{n} \sum_{i=1}^n \Delta_{(x_i, y_i)}$.

Robustness

What is the impact on $S(P) = f_{P,\lambda}$ due to violations from
 (X_i, Y_i) i.i.d. $\sim P$, $P \in \mathcal{M}_1$ unknown ?



Roadmap



Influence Function

Definition (Hampel, '68, Hampel et al. '86)

The influence function of S at P is given by

$$\text{IF}(z; S, P) := \lim_{\epsilon \downarrow 0} \frac{S((1 - \epsilon)P + \epsilon\Delta_z) - S(P)}{\epsilon},$$

in those z where this limit exists.

If Gâteaux derivative $\nabla^G(z; S, P)$ exists:

$\nabla^G = \text{IF}$ and IF is linear and continuous

Goal: **Bounded IF**

Bouligand differentiability

Bouligand-derivative

$f : X \rightarrow Z$ is **Bouligand-differentiable** at $x_0 \in X$, if \exists a positive homogeneous function $\nabla^B f(x_0) : X \rightarrow Z$ such that

$$f(x_0 + h) = f(x_0) + \nabla^B f(x_0)(h) + o(h),$$

i.e.

$$\lim_{h \downarrow 0} \frac{\|f(x_0 + h) - f(x_0) - \nabla^B f(x_0)(h)\|_Z}{\|h\|_X} = 0.$$

Bouligand differentiability

Georges L. Bouligand

°1889 – †1979 - France

Career: Lycée de Rennes

Université de Poitiers

Sorbonne

Research: Geometry infinitesimal, vectorial, analytical

Analysis differential equations, harmonic fcts

Group theory

Topology

Mechanics

Introduced: Bouligand-Minkowski dimension

Contingent/Tangent cone

Strong approximation

$f : X \rightarrow Z$ **strongly approximates** $F : X \times Y \rightarrow Z$ in x at (x_0, y_0) (notation: $f \approx_x F$) if $\forall \varepsilon > 0 \exists$ neighborhoods $\mathcal{N}(x_0)$ of x_0 and $\mathcal{N}(y_0)$ of y_0 such that $\forall x, x' \in \mathcal{N}(x_0), \forall y \in \mathcal{N}(y_0)$

$$\| (F(x, y) - f(x)) - (F(x', y) - f(x')) \|_Z \leq \varepsilon \|x - x'\|_X.$$

Strong Bouligand-derivative

$F : X \times Y \rightarrow Z$ has partial B-derivative $\nabla_1^B F(x_0, y_0)$ w.r.t. x at (x_0, y_0) . Then $\nabla_1^B F(x_0, y_0)$ is **strong** if

$$F(x_0, y_0) + \nabla_1^B F(x_0, y_0)(x - x_0) \approx_x F$$

at (x_0, y_0) .

Robinson (1991)



Bouligand Influence Function

BIF (C&VM '07)

The **Bouligand influence function** (BIF) of a function $S : \mathcal{M}_1 \rightarrow \mathcal{H}$ for a distribution P in the direction of a distribution $Q \neq P$ is the special B-derivative (if it exists)

$$\lim_{\varepsilon \|Q - P\| \downarrow 0} \frac{\|S((1 - \varepsilon)P + \varepsilon Q) - S(P) - \text{BIF}(Q; S, P)\|_{\mathcal{H}}}{\varepsilon \|Q - P\|} = 0.$$

If BIF exists and $Q = \Delta_z$, then Hampel's IF exists and $\text{BIF} = \text{IF}$

Goal: **Bounded BIF**

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Goal: **Bounded BIF**

Main result

Assumptions

- $X \subset \mathbb{R}^d$, $Y \subset \mathbb{R}$ closed sets,
- \mathcal{H} is RKHS with **bounded**, measurable kernel k ,
- $f_{P,\lambda} \in \mathcal{H}$,
- $L : Y \times \mathbb{R} \rightarrow [0, \infty)$ **convex** and **Lipschitz continuous** w.r.t. the 2^{nd} argument with uniform Lipschitz constant $|L|_1 := \sup_{y \in Y} |L(y, \cdot)|_1 \in (0, \infty)$,
- L has measurable partial B-derivatives w.r.t. to the 2^{nd} argument with $\kappa_1 := \sup_{y \in Y} \|\nabla_2^B L(y, \cdot)\|_\infty \in (0, \infty)$,
 $\kappa_2 := \sup_{y \in Y} \|\nabla_{2,2}^B L(y, \cdot)\|_\infty < \infty$,

Assumptions

- $\delta_1 > 0, \delta_2 > 0,$
- $\mathcal{N}_{\delta_1}(f_{P,\lambda}) := \{f \in \mathcal{H}; \|f - f_{P,\lambda}\|_{\mathcal{H}} < \delta_1\},$
- $\lambda > \frac{1}{2}\kappa_2 \|\Phi\|_{\mathcal{H}}^3,$
- P, Q probability measures on $(X \times Y, \mathcal{B}(X \times Y))$ with $\mathbb{E}_P|Y| < \infty$ and $\mathbb{E}_Q|Y| < \infty.$
- Define $G : (-\delta_2, \delta_2) \times \mathcal{N}_{\delta_1}(f_{P,\lambda}) \rightarrow \mathcal{H},$

$$G(\varepsilon, f) := 2\lambda f + \mathbb{E}_{(1-\varepsilon)P+\varepsilon Q} \nabla_2^B L(Y, f(X)) \Phi(X),$$

- $G(0, f_{P,\lambda}) = 0$ and $\nabla_2^B G(0, f_{P,\lambda})$ is **strong**.

Theorem (C&VM '07)

Then $\text{BIF}(Q; S, P)$ with $S(P) := f_{P,\lambda}$

- 1 exists,
- 2 equals

$$T^{-1} \left(\mathbb{E}_P \nabla_2^B L(Y, f_{P,\lambda}(X)) \Phi(X) - \mathbb{E}_Q \nabla_2^B L(Y, f_{P,\lambda}(X)) \Phi(X) \right),$$

where $T : \mathcal{H} \rightarrow \mathcal{H}$ with

$T = 2\lambda \text{id}_{\mathcal{H}} + \mathbb{E}_P \nabla_{2,2}^B L(Y, f_{P,\lambda}(X)) \langle \Phi(X), \cdot \rangle_{\mathcal{H}} \Phi(X)$, and

- 3 is bounded.

Examples

The assumptions of the theorem are valid and thus $\text{BIF}(Q; S, P)$ exists and is bounded, if

ϵ -insensitive loss L_ϵ , pinball loss L_τ

$\forall \delta > 0 \exists$ positive constants ξ_P, ξ_Q, c_P , and c_Q such that $\forall t \in \mathbb{R}$ with $|t - f_{P,\lambda}(x)| \leq \delta \|k\|_\infty$ the following inequalities hold $\forall a \in [0, 2\delta \|k\|_\infty]$ and $\forall x \in X$:

$$P(Y \in [t, t + a] \mid x) \leq c_P a^{1+\xi_P}$$

$$Q(Y \in [t, t + a] \mid x) \leq c_Q a^{1+\xi_Q}.$$

The assumptions of the theorem are valid and thus $\text{BIF}(Q; S, P)$ exists and is bounded, if

Huber loss L_{Huber}

$$\begin{aligned} \forall x \in X: \\ & \mathbb{P}(Y \in \{f_{P,\lambda}(x) - c, f_{P,\lambda}(x) + c\} \mid x) \\ &= \mathbb{Q}(Y \in \{f_{P,\lambda}(x) - c, f_{P,\lambda}(x) + c\} \mid x) \\ &= 0. \end{aligned}$$

Logistic loss L_{log}

No special assumptions on the probabilities needed.

Conclusions

Bouligand Influence Function

- If BIF exists and $Q = \Delta_z$: $\text{BIF} = \text{IF}$
- B-derivative: pos. homog., chain rule, implicit funct. thm

Support Vector Machines

- Non-parametric and flexible
- Able to learn
- Robust: $\text{BIF}(Q; T, P)$ bounded for regression if $\nabla_2^B L$ and k bounded
- Applications: insurance tariffs, credit scoring in banks, fraud detection, data mining, genomics, ...

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More on the theorem

For the proof of the theorem we showed:

- i. For some χ and each $f \in \mathcal{N}_{\delta_1}(f_{P,\lambda})$, $G(\cdot, f)$ is Lipschitz continuous on $(-\delta_2, \delta_2)$ with Lipschitz constant χ .
- ii. G has partial B-derivatives with respect to ε and f at $(0, f_{P,\lambda})$.
- iii. $\nabla_2^B G(0, f_{P,\lambda})(\mathcal{N}_{\delta_1}(f_{P,\lambda}) - f_{P,\lambda})$ is a neighborhood of $0 \in \mathcal{H}$.
- iv. $\delta(\nabla_2^B G(0, f_{P,\lambda}), \mathcal{N}_{\delta_1}(f_{P,\lambda}) - f_{P,\lambda}) =: d_0 > 0$.

- v.** For each $\xi > d_0^{-1}\chi$ there exist $\delta_3, \delta_4 > 0$, a neighborhood $\mathcal{N}_{\delta_3}(f_{P,\lambda}) := \{f \in \mathcal{H}; \|f - f_{P,\lambda}\|_{\mathcal{H}} < \delta_3\}$, and a function $f^* : (-\delta_4, \delta_4) \rightarrow \mathcal{N}_{\delta_3}(f_{P,\lambda})$ satisfying
- v.1)** $f^*(0) = f_{P,\lambda}$.
 - v.2)** $f^*(\cdot)$ is Lipschitz continuous on $(-\delta_4, \delta_4)$ with Lipschitz constant $|f^*|_1 = \xi$.
 - v.3)** For each $\varepsilon \in (-\delta_4, \delta_4)$ is $f^*(\varepsilon)$ the unique solution of $G(\varepsilon, f) = 0$ in $(-\delta_4, \delta_4)$.
 - v.4)** It holds

$$\nabla^B f^*(0)(u) = (\nabla_2^B G(0, f_{P,\lambda}))^{-1} (-\nabla_1^B G(0, f_{P,\lambda})(u)).$$