

# Qualitatively Robust Nonparametric Regression By Support Vector Machines

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# Nonparametric Regression

$$Y = f_0(X) + \varepsilon$$

with

- ▶  $Y$ : output variable (observable)
- ▶  $X$ : input variable (observable)
- ▶  $f_0$ : regression function (unknown)
- ▶  $\varepsilon$ : error term (not observable)

**Goal:** Estimation of the unknown regression function  $f_0$

# Qualitative Robustness

# Qualitative Robustness – Parametric Statistics

## Parametric Model

$$(P_\theta)_{\theta \in \Theta}, \quad \Theta \subset \mathbb{R}^d$$

and

$$Z_i \sim P_{\theta_0} \text{ i.i.d.}, \quad \theta_0 \in \Theta$$

## Estimator

$$S_n : \mathcal{Z}^n \rightarrow \Theta, \quad (z_1, \dots, z_n) \mapsto S_n(z_1, \dots, z_n)$$

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**Robustness:** different notions

small model violations  
small errors in the data } should not change the result too much

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- ▶ Small errors in the data
  - ▶ Small errors in many of the data points (rounding etc.)
  - ▶ Large errors in a few data points (gross errors, outliers)

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- ▶ “should not change the result too much”

$P_\theta$ : model distribution

$Q$ : real distribution

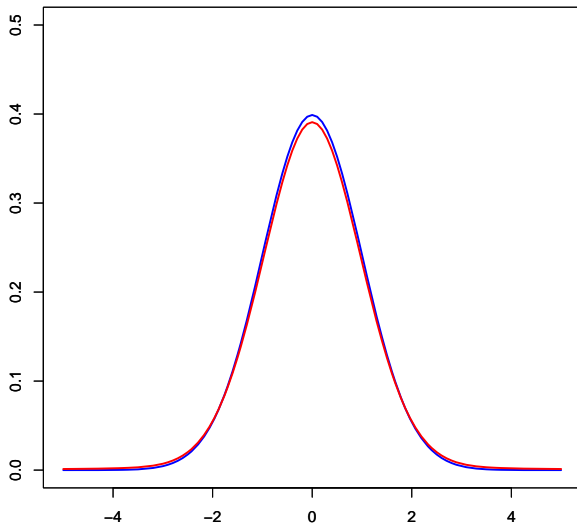
$$Q \text{ close to } P_\theta \quad \longrightarrow \quad S_n(Q^m) \text{ close to } S_n(P_\theta)$$

$S_n(P_\theta)$ : assumed distribution of the estimator

$S_n(Q^m)$ : real distribution of the estimator

(distribution of the estimator = performance of the estimator)

## Qualitative Robustness – Example

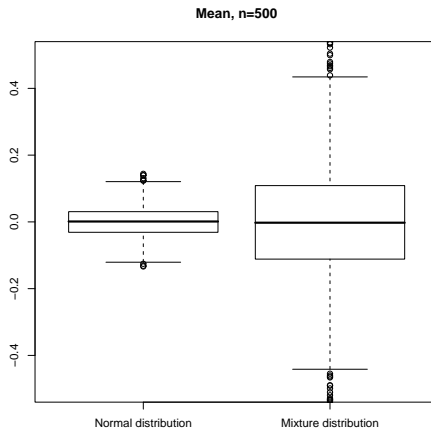




## Qualitative Robustness – Example

"mean" applied in 1000 runs

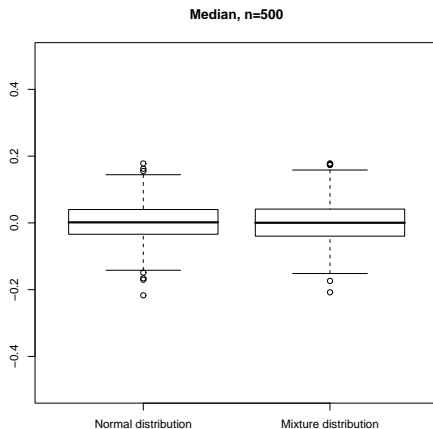
each run consists of a sample with 500 data points



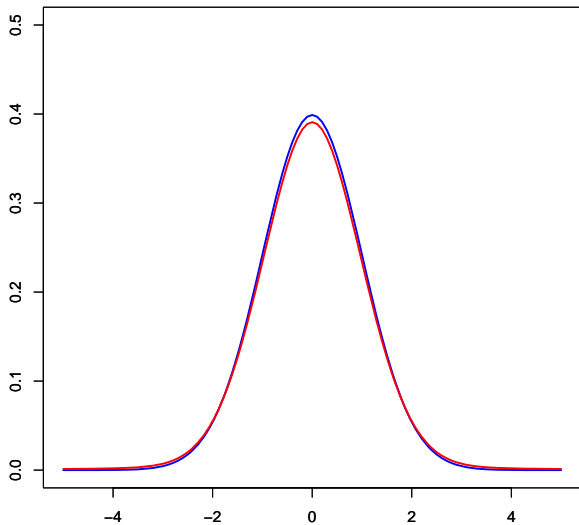
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## Qualitative Robustness – Example



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The sequence of estimators  $(S_n)_{n \in \mathbb{N}}$  is **qualitatively robust** if

$\forall P \forall \epsilon > 0 \exists \delta > 0$  such that  $\forall Q$  with  $d_{\text{Pro}}(Q, P) < \delta$

$$\sup_{n \in \mathbb{N}} d_{\text{Pro}}(S_n(Q^n), S_n(P^n)) < \epsilon$$

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Prokhorov distance between probability measures  $Q$  and  $P$ :

$$d_{\text{Pro}}(Q, P) = \inf \{ \delta > 0 \mid Q(A) \leq P(A^\delta) + \delta \forall A \}$$

$$A^\delta = \{ z \mid \inf_{z' \in A} d(z, z') < \delta \}$$

# Qualitatively Robust Nonparametric Regression

## Nonparametric Regression

$$Y_i = f_0(X_i) + \varepsilon_i, \quad i \in \{1, \dots, n\}$$

and

$$(X_i, Y_i) \sim P \quad \text{i.i.d.}$$

**Goal:** Estimation of  $f_0 : \mathcal{X} \rightarrow \mathcal{Y}$

**Estimator:**

$$S_n : (\mathcal{X} \times \mathcal{Y})^n \rightarrow H$$

$H$ : a large set of functions  $f : \mathcal{X} \rightarrow \mathcal{Y}$

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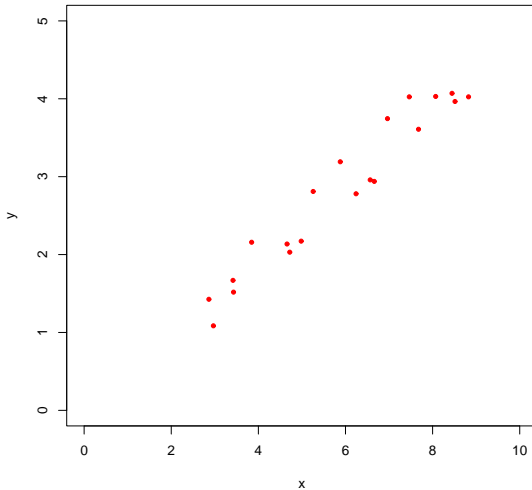
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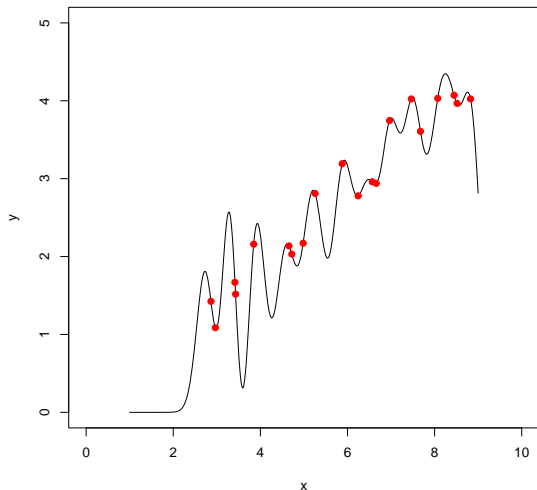
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## Qualitative Robustness and SVMs

### Support Vector Machines

$$S_n : (\mathcal{X} \times \mathcal{Y})^n \rightarrow H,$$

$$((x_1, y_1), \dots, (x_n, y_n)) \mapsto \arg \inf_{f \in H} \frac{1}{n} \sum_{i=1}^n L(y_i, f(x_i)) + \lambda \|f\|_H^2$$

with  $H$  a Hilbert space of functions  $f : \mathcal{X} \rightarrow \mathbb{R}$

### Qualitative Robustness:

A sequence of estimators  $(S_n)_{n \in \mathbb{N}}$  is called **qualitatively robust** if

$$\forall P \quad \forall \epsilon > 0 \quad \exists \delta > 0 \text{ such that } \forall Q \text{ with } d_{\text{Pro}}(Q, P) < \delta$$

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## Qualitative Robustness and SVMs

**Cuevas (1988):**

If a sequence of estimators

$$S_n : (\mathcal{X} \times \mathcal{Y})^n \rightarrow H, \quad n \in \mathbb{N},$$

can be represented by a functional

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i.e.

$$S_n((x_1, y_1), \dots, (x_n, y_n)) = S\left(\frac{1}{n} \sum_{i=1}^n \delta_{(x_i, y_i)}\right) \quad \forall (x_i, y_i) \in \mathcal{X} \times \mathcal{Y}$$

for every  $n \in \mathbb{N}$

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then

the sequence of estimators  $(S_n)_{n \in \mathbb{N}}$  is qualitatively robust.



## Qualitative Robustness and SVMs

In case of support vector machines

$$S_n((x_1, y_1), \dots, (x_n, y_n)) = \arg \inf_{f \in H} \frac{1}{n} \sum_{i=1}^n L(y_i, f(x_i)) + \lambda \|f\|_H^2,$$

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$$S(P) = \arg \inf_{f \in H} \int L(y, f(x)) P(d(x, y)) + \lambda \|f\|_H^2 \quad \forall P.$$

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It remains to be proven:

$$P_n \xrightarrow[n \rightarrow \infty]{} P_0 \text{ weakly} \quad \Rightarrow \quad \left\| S(P_n) - S(P_0) \right\|_H \xrightarrow[n \rightarrow \infty]{} 0$$

## Qualitative Robustness and SVMs

### Assumptions:

- ▶  $\mathcal{X}$  a Polish space,  $\mathcal{Y} \subset \mathbb{R}$  closed
- ▶  $L : \mathcal{Y} \times \mathbb{R} \rightarrow [0, \infty)$  continuous
  - ▶  $t \mapsto L(y, t)$  convex for every  $t \in \mathbb{R}$
  - ▶  $t \mapsto L(y, t)$ ,  $y \in \mathcal{Y}$ , uniformly Lipschitz continuous
- ▶ the reproducing kernel

$$k : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}$$

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**Main Result:** The functional

$$P \mapsto S(P) = \arg \inf_{f \in H} \int L(y, f(x)) P(d(x, y)) + \lambda \|f\|_H^2$$

is continuous.

## Corollaries

**Main Result:** The functional

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**Corollary 1:**

Support vector machines

$$S_n : (\mathcal{X} \times \mathcal{Y})^n \rightarrow H,$$

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are qualitatively robust.

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**Corollary 2:**

Support vector machines

$$\begin{aligned} S_n : \quad (\mathcal{X} \times \mathcal{Y})^n &\rightarrow H, \\ ((x_1, y_1), \dots, (x_n, y_n)) &\mapsto \arg \inf_{f \in H} \frac{1}{n} \sum_{i=1}^n L(y_i, f(x_i)) + \lambda \|f\|_H^2 \end{aligned}$$

depend on the data **continuously**.

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**Corollary 3:**

Strong consistency:

$$S_n \xrightarrow{P\text{-a.s.}} S(P) \quad \text{for } n \rightarrow \infty$$

## References

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The handout to this talk is also available on my homepage

<http://www.staff.uni-bayreuth.de/~btms04/index.html>