

Higher Order Optimal Influence Curves

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Ideal Setup

Setup: inference on parameter θ in a model for i.i.d. observations

$$\mathcal{P} = \{P_\theta \mid \theta \in \Theta\} \quad \Theta \subset \mathbb{R}^k, \quad \mathcal{P} \text{ "smooth"}$$

- common robust technique:
use first order *von-Mises (vM) expansion*

Definition

influence curves at P_0 :

$$IC_{\tau, P_0}(T) = \lim_{\epsilon \rightarrow 0} \frac{E_{P_0} \left[\tau \left(\frac{T - T_0}{\epsilon} \right) \right] - \tau(T_0)}{\epsilon}$$

asymptotically linear estimators:

$$T - T_0 = \int_0^1 \dot{T}(t) dt + o_p(n^{-1/2})$$

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Definition

influence curves at P_θ :

$$\Psi_2(\theta) = \{\psi_\theta \in L_2^k(P_\theta) \mid \mathbb{E}_\theta \psi_\theta = 0, \mathbb{E}_\theta \psi_\theta \Lambda_\theta^\tau = \mathbb{I}_k\}$$

asymptotically linear estimators:

$$\sqrt{n}(S_n - \theta) = \frac{1}{\sqrt{n}} \sum_{i=1}^n \psi_\theta(x_i) + o_{P_\theta^n}(n^0)$$

Infinitesimal Robust Setup

Shrinking neighborhoods (Rieder[81,94], Bickel[83])

$$U_c(\theta, r, n) = \left\{ (1 - r/\sqrt{n})_+ P_\theta + (1 \wedge r/\sqrt{n}) R \mid R \in \mathcal{M}_1(\mathcal{A}) \right\}$$

Robust optimality problem: $\sup_{Q \in U_c} \text{MSE}_Q(\psi_\theta) = \min!$

here: $\sup_{Q \in U_c} \text{MSE}_Q(\psi_\theta) = \mathbb{E}_\theta |\psi_\theta|^2 + r^2 \sup |\psi_\theta|^2$

Thm.s 5.5.1 and 5.5.7 (b), Rieder[94]

unique solution is an IC $\tilde{\eta}_\theta$ of Hampel-type (HC-1), i.e.;

$$\tilde{\eta}_\theta = (A_\theta \Lambda_\theta - a_\theta) w \quad w = \min \{1, b_\theta / |A_\theta \Lambda_\theta - a_\theta|\}$$

with $A_\theta, a_\theta, b_\theta$ such that $\mathbb{E}_\theta \tilde{\eta}_\theta = 0$, $\mathbb{E}_\theta \tilde{\eta}_\theta \Lambda_\theta^\tau = \mathbb{I}_k$, and

$$\text{(MSE)} \quad r^2 b_\theta = \mathbb{E}_\theta (|A_\theta \Lambda_\theta - a_\theta| - b_\theta)_+$$

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Limitations of First Order Approach

- So far: asymptotics is of first order, for both ALE and MSE
- Limitations (not a topic today): No indication
 - for the quality/speed of the convergence — to what degree do radius r , sample size n and clipping height b affect the approximation?
 - which construction (achieving an optimally-robust IC asymptotically) to take
- Questions for this talk:
 - (Q1) *Can we enhance finite sample performance using refined asymptotics?*
 - (Q2) *Hampel's conjecture:*
—with regard to the corners of (first-order) MSE solution—
Should not a finitely optimal IC be smooth?

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Does first order optimality imply second order optimality?

Classical Optimality (of IC of MLE):

- first order setup:
 - risk-independence in Asympt. Convolution Theorem / for all “bowl-shaped” risks in Asympt. Minimax Theorem
- second order setup: *Pfanzagl's* catchword
“First order optimality implies second order optimality”

Robust Optimality (of ICs from class HC-1):

- first order setup (R.& Rieder [& Kohl] (2004/2007))
 - risk-independence of the class
 - risk-dependence of the member within HC-1
 - radius-minimax ICs: risk-independence of the optimal member for all “homogeneous” risks
- second order setup:

(Q3) Does Pfanzagl's catchword apply to the robust setup, and if so in which way?

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Uniform Expansions of the MSE

Theorem (R. [05(a,b,c)])

Let $\theta \mapsto \eta_\theta$ be smooth in $L_1(P_\theta)$,

S_n be an M - or a k -step-estimator to η_θ , and

let starting estim. $\theta_n^{(0)}$ for the k -step-estimator be

- uniformly $n^{1/4+\delta}$ -consistent on \tilde{U}_c for some $\delta > 0$
- uniformly square-integrable in n and on \tilde{U}_c

Then

$$\max \text{MSE}(S_n) := n \sup_{Q_n \in \tilde{U}_c(r)} \text{MSE}(S_n)$$

$$= A_0 + \frac{r}{\sqrt{n}} A_1 + \frac{1}{n} A_2 + o\left(\frac{1}{n}\right)$$

for $A_0 = E_\theta |\eta_\theta|^2 + r^2 \sup |\eta_\theta|^2$ and A_1, A_2 are constants depending on η_θ, r , and, for k -step-est., also on $\theta_n^{(0)}$

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Second Order Optimality – Symmetric Case

Corollary

Let P_θ and ψ be symmetric:

Then $A_1 = 2r^2 b^2 + v^2 + b^2$

i.e., a convex and isotone function in $\|\eta\|_{L_2}$ and $\|\eta\|_{L_\infty}$ — the same terms arising in first order term A_0 .

Consequence:

(ad Q3) Pfanzagl's "rule" for class HC-1:

Second order optimal (s-o-o) IC is of HC-1-form

$$A \wedge \min\{1, c_1/|\Lambda|\}$$

but with adjusted s-o-o clipping height c_1 determined as

$$r^2 c_1 \left(1 + \frac{r^2 + 1}{r^2 + r\sqrt{n}} \right) = E(|\Lambda| - c_1)_+$$

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Second Order Optimal Clipping

If $h(c) := E(|\Lambda| - c)_+$ is differentiable in the f-o-o c_0 ,

$$c_1 = c_0 \left(1 - \frac{1}{\sqrt{n}} \frac{r^3 + r}{r^2 - h'(c_0)} \right) + o\left(\frac{1}{\sqrt{n}}\right)$$

\implies As $h' < 0$, $c_1 < c_0$ always

i.e.; **first order asymptotics is too optimistic**

- as c_1 is optimal, s-o risk behaves locally as a parabola with vertex in c_1 ; hence the risk-improvement of c_1 compared to c_0 is $O(1/n)$
- same goes for t-o-o clipping height $c_2 \implies$ risk-improvement of c_2 compared to c_1 is $O(1/n^2)$

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Optimal c 's and corresp. (num.) exact maxMSE at $\mathcal{N}(\theta, 1)$ — $n = 20, r = 0.3$ —:

	c	exact risk:		asymptotic risk:		
		$\text{relMSE}_n^{\text{ex}}$	$\text{maxMSE}_n^{\text{ex}}$	A_0	$A_0 + \frac{r}{\sqrt{n}} A_1$	$A_0 + \frac{r}{\sqrt{n}} A_1 + \frac{1}{n} A_2$
Median	0+	16.413%	1.911	1.712	1.942	1.875
η_{c_0}	1.213	1.548%	1.667	1.290	1.556	1.615
η_{c_1}	1.017	0.117%	1.643	1.299	1.544	1.596
η_{c_2}	0.972	0.017%	1.642	1.299	1.544	1.596
$\eta_{c_{\text{FZY}}}$	0.991	0.049%	1.642	1.301	1.545	1.596
$\eta_{c_{\text{ex}}}$	0.939	—	1.641	1.307	1.545	1.596

c_0	f-o-o: by equation we just saw
c_1	s-o-o: by equation we just saw
c_2	third order: num. optimization of MSE in HC-1
c_{FZY}	num. optimization of a proposal by Fraiman et al.
c_{ex}	num. optimization of the (num.) exact MSE

One dimensional Scale

Corollary (Second order optimality for one-dim. scale)

Let S_n be two-step estimator to IC η_θ
 (with e.g. MAD as starting estimator)

Then

$$\max \text{MSE}(S_n) = A_0 + \frac{r}{\sqrt{n}} A_1 + o\left(\frac{1}{\sqrt{n}}\right)$$

$$\text{for } A_0 = v_0^2 + r^2 b^2, \quad v_0^2 = \mathbb{E}_\theta \eta_\theta^2, \quad b = \sup |\eta_\theta|$$

$$A_1 = v_0^2 + b^2(1 + 2r^2) + b \left| l_2 (3v_0^2 + r^2 b^2) + 2v_1 \right|$$

$$\text{for } l_2 = \frac{d^2}{dt^2} \mathbb{E}_\theta \eta_t \Big|_{t=\theta}, \quad v_1 = \frac{d}{dt} \mathbb{E}_\theta \eta_t^2 \Big|_{t=\theta}$$

Shifting differentiation to P_θ — integration by parts and scale invariance:

$$A_1 = \mathbb{E} \eta^2 + b^2(1 + 2r^2) + b \left| \mathbb{E} \eta^2 (4 - 2\Lambda) + \mathbb{E} \eta L_2 (3 \mathbb{E} \eta^2 + r^2 b^2) \right|$$

$$\text{for } \Lambda = \frac{\partial}{\partial \theta} \log p_\theta, \quad L_2 = \frac{\partial^2}{\partial \theta^2} \log p_\theta$$

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Second Order Optimality Problems

$$\boxed{\text{MSE-2}} \quad F_n(\eta) := A_0(\eta) + \frac{r}{\sqrt{n}} A_1(\eta) = \min! \quad \eta \text{ IC}, \eta \in L_3(P)$$

Structure of the problem suited for convex optimization

- admitted functions form convex set
- F_n is coercive \rightsquigarrow restriction to some bounded L_∞ -ball possible
- eventually in n , F_n is weakly lower semicontinuous in L_3 and strictly convex \implies unique minimum solution exists
- Slater condition fulfilled \rightsquigarrow Lagrange multipliers exist
- equivalence to Hampel-problem: for $r_n = \frac{r}{\sqrt{n+r}}$ and

$$H_n(\eta) = \mathbb{E} \eta^2 + r_n b \left(2 \mathbb{E} \eta^2 (2 - \Lambda) + \mathbb{E} \eta L_2 (3 \mathbb{E} \eta^2 + r^2 b^2) \right)$$

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Solution for fixed b

Solution to HP-1 for fixed b
“Hampel-type-1” (HC-1)

$$\hat{\eta} = Y \min\left\{1, \frac{b}{|Y|}\right\}$$

for

$$Y = A\Lambda - a$$

with scores Λ , Lagrange multipliers A , a , and bias bound b

Gaussian case:

$$Y = Ax^2 - a$$

Solution for fixed b

Solution to HP-2 for fixed b
 “Hampel-type-2” (HC-2)

$$\hat{\eta} = Y_n \min\left\{1, \frac{b}{|Y_n|}\right\}, \quad Y_n = \frac{Y - r_n b L_2(r^2 b^2 + 3v_0^2)/2}{1 + r_n b(4 - 2\Lambda + 3l_2)}$$

for

$$Y = A\Lambda - a, \quad v_0^2 = E Y^2, \quad l_2 = E L_2$$

with scores Λ , Lagrange multipliers A , a , and bias bound b ,
 and second order radius term $r_n = r/(\sqrt{n} + r)$

Gaussian case:

$$Y_n = \frac{Ax^2 - a - r_n b(x^4 - 5x^2 + 2)(3v_0^2 + r^2 b^2)/2}{1 + r_n b(6 - 2x^2 + 3l_2)}$$

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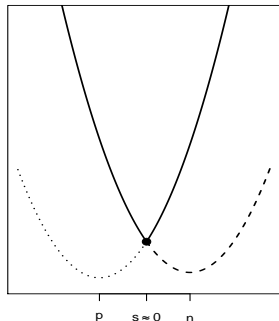
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Problem:

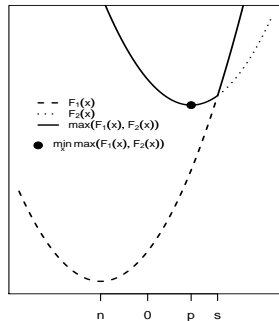
- $\left| \cdot \right|$ -expression in s-o-term A_1 in $\max\text{MSE}$:
 b in f-o-term A_0 may be induced by positive or negative bias
- i.e.; $\max\text{MSE}(\eta) = A_0(\eta) + r/\sqrt{n} \max(A_1(\eta, -b), A_1(\eta, b))$

Positive or Negative Bias?

Situation 1



Situation 2



- to be checked for any second-order MSE-solution
- numerically for Gaussian scale case:
left situation (optimum in intersection point of parabolas)

Hampel-type ICs Second Order Optimal?

(ad Q3) Possible gain in (s-o-)maxMSE w.r.t. s-o-clipping-adjusted HC-1-type IC $< 10^{-5}$!!

—consequence:

- may stay in class HC-1 of Hampel-type ICs
- simply adjust clipping height w.r.t. first order optimal solution
- Pfanzagl's "rule" for **class HC-1**

(ad Q2) General feature:

- no matter whether optimal solution $\hat{\eta}$ is of type HC-1 or HC-2:

Solution involves clipping!

- if $Y'_{[n]} \neq 0$ in clipping points: *non-smooth* optimal IC
- argument applies to arbitrary asymptotic order (3rd, 4th, ...)

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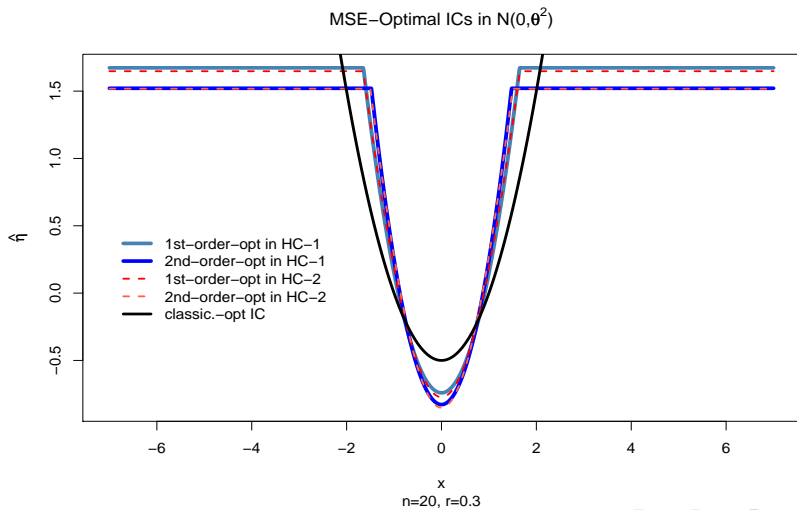
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Second Order MSE-Optimal IC to $r = 0.3$



Optimal b 's and corresp. empirical maxMSE

emp. results for $\mathcal{N}(0, \theta^2)$ at $n = 20$, $r = 0.3$ at $M = 90000$ runs:

	b	empirical risk:			asymptotic risk:	
		relMSE $_n^{\text{sim}}$	maxMSE $_n^{\text{sim}}$		A_0	$A_0 + \frac{r}{\sqrt{n}}A_1$
MAD	1.166	24.18%	1.822	[1.801; 1.843]	1.223	1.487
η_{b_0}	1.671	27.48%	1.870	[1.836; 1.905]	0.892	1.075
η_{b_1} (HC-1)	1.530	8.75%	1.596	[1.572; 1.619]	0.905	1.057
η_{b_1} (HC-2)	1.531	8.63%	1.594	[1.571; 1.617]	0.906	1.060
$\eta_{b_{\text{sim}}}$	1.346	—	1.467	[1.450; 1.484]	0.945	1.105

b_0 f-o-o: optimized A_0 within HC-1

b_1 s-o-o: optimized $A_0 + \frac{r}{\sqrt{n}}A_1$ within HC-1/HC-2

b_{sim} num. optimization of the (empirical) maxMSE within HC-1

Consequences:

- first order asymptotics too optimistic

(ad Q1) considerable enhancement by 2nd order asymptotics —

- but: still room for improvement by 3rd order asymptotics

One dimensional Location and Scale for symmetric F

Corollary (Second order optimality for one-dim. location and scale)

Let S_n be two-step estimator to IC η_θ (with e.g. (Median, MAD) as starting estimator)

Then

$$\begin{aligned} \max \text{MSE}(S_n) &= n \sup_{Q_n \in \tilde{U}_c(r)} \text{MSE}(S_n) \\ &= \boxed{A_0 + \frac{r}{\sqrt{n}} A_1 + o\left(\frac{1}{\sqrt{n}}\right)} \end{aligned}$$

for $A_0 = E_\theta |\eta_\theta|^2 + r^2 b_\theta^2$, $b_\theta = \sup |\eta_\theta|$ and

A_1 only slightly more complicated than in pure scale case

Structure of the Solution

- similar arguments as in scale case
- location component is odd, scale component even
- adaptivity also holds for second order asymptotics (but nuisance part has to have bounded IC)
- positive/negative bias: here right situation in the parabola picture (optimum in a vertex of a parabola)

(ad Q3) possible gain in (s-o-)maxMSE w.r.t. s-o-clipping-adjusted HC-1 IC $\ll 1\%$!! —hence grossly speaking:

- may stay in class HC-1 of Hampel-type ICs
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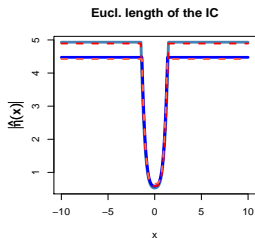
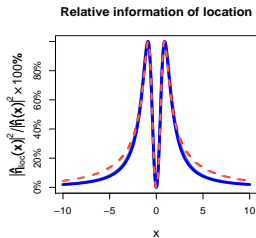
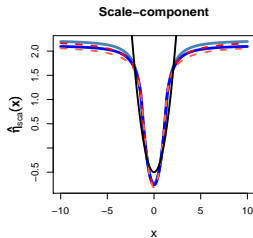
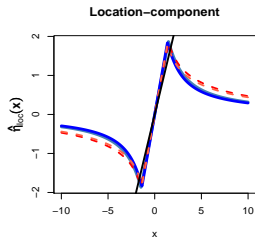
Structure of the Solution

- similar arguments as in scale case
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Second Order MSE-Optimal IC to $r = 0.3$



MSE-Optimal ICs in $N(\theta_{loc}, \theta_{sca}^2)$

Sample size $n = 20$
 (starting) radius $r = 0.3$
 (actual radius 0.067)

- 1st-order-opt in HC-1
- 2nd-order-opt in HC-1
- - 1st-order-opt in HC-2
- - 2nd-order-opt in HC-2
- classic-opt IC

(ad Q2)

coordinate-wise:

$\hat{\eta}_{loc}$ $\hat{\eta}_{sca}$: **smooth**

Euclidean length:

$\sqrt{\hat{\eta}_{loc}^2 + \hat{\eta}_{sca}^2}$: **non-smooth!**

Optimal b 's and corresp. empirical maxMSE

emp. results for $\mathcal{N}(\theta_{loc}, \theta_{sca}^2)$ at $n = 20$, $r = 0.3$ at $M = 90000$ runs:

	b	empirical risk:			asymptotic risk:	
		relMSE $_n^{\text{sim}}$	maxMSE $_n^{\text{sim}}$		A_0	$A_0 + \frac{r}{\sqrt{n}} A_1$
(Median;MAD)	1.713	22.38%	3.747	[3.716; 3.777]	3.057	3.629
η_{b_0}	2.221	37.37%	4.205	[4.117; 4.294]	2.154	2.768
η_{b_1} (HC-1)	2.116	23.52%	3.782	[3.713; 3.850]	2.161	2.757
η_{b_1} (HC-2)	2.103	19.51%	3.659	[3.590; 3.720]	2.167	2.753
$\eta_{b_{\text{sim}}}$	1.744	—	3.061	[3.033; 3.090]	2.406	3.069

b_0 f-o-o: optimized A_0 within HC-1

b_1 s-o-o: optimized $A_0 + \frac{r}{\sqrt{n}} A_1$ within HC-1/HC-2

b_{sim} num. optimization of the (empirical) maxMSE within HC-1

Consequences:

- again: first order asymptotics too optimistic

(ad Q1) again: enhancement by 2nd order asymptotics —

- but even 2nd order asymptotics probably not enough

Summary: Answers to (Q1)-(Q3)

(Q1) *Can we enhance finite sample performance using refined asymptotics?*

Yes, we can — for location only a little, for scale and location/scale considerably. . .





(Q2) Hampel's conjecture: *“Should not a finitely optimal IC be smooth?”*

Regarding higher order asymptotics: **No**, they should not.

(Q3) Does Pfanzagl's catchword *“First order optimality implies second order optimality”* apply to the robust setup, and if so in which way? Grossly speaking:

Yes, it does **classwise** for class (HC-1). However, first order optimal clipping height is **too optimistic**.

Bibliography

-  H. Rieder (1994): *Robust Asymptotic Statistics*. Springer.
-  P. Ruckdeschel (2005(a)): Higher order asymptotics for the MSE of M estimators on shrinking neighborhoods. Submitted. Also available in <http://www.uni-bayreuth.de/departments/math/org/mathe7/RUCKDESCHEL/pubs/mest1.pdf>.
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-  P. Ruckdeschel (2005(c)): Higher order asymptotics for the MSE of k -step-estimators on shrinking neighborhoods. In preparation.

For references please confer the handout to this talk on my web-page.

Thank you for your attention!

Uniform Expansions of the MSE II

Exact expressions for term A_1 for 1-step-estimator

Let η_θ bounded and two times differentiable in $L_1(P_\theta)$,

$$\theta_n^{(0)} = \theta + \frac{1}{n} \sum \tilde{\eta}_\theta(x_i) + o_{L_1(\tilde{U}_c)}(n^{-1/2}) \text{ for a bounded IC } \tilde{\eta}_\theta,$$

Then

$$\begin{aligned} A_1 &= 2 \operatorname{Cov}_\theta(\eta_\theta, \tilde{\eta}_\theta) - \operatorname{Var}_\theta \eta_\theta^2 + b_\theta^2 \\ &\quad + 2b_\theta \frac{d}{dt} \operatorname{Cov}_\theta(\eta_t, \tilde{\eta}_\theta) \Big|_{t=\theta} + 2\tilde{b}_\theta \frac{d}{dt} \operatorname{Var}_\theta \eta_t \Big|_{t=\theta} \\ &\quad + \frac{d^2}{dt^2} \operatorname{E}_\theta \eta_t \Big|_{t=\theta} \left[b_\theta \operatorname{Var}_\theta \tilde{\eta}_\theta + 2\tilde{b}_\theta \operatorname{Cov}_\theta(\eta_\theta, \tilde{\eta}_\theta) \right] \\ &\quad + r^2 \tilde{b}_\theta b_\theta \left[2 + \tilde{b}_\theta \frac{d^2}{dt^2} \operatorname{E}_\theta \eta_t \Big|_{t=\theta} \right] \end{aligned}$$

where $b_\theta = \sup |\eta_\theta|$, $\tilde{b}_\theta = \limsup_{\epsilon \downarrow 0} \sup |\tilde{\eta}_\theta| \mathbb{I}(|\eta_\theta| \geq b_\theta - \epsilon)$

M-est put $\tilde{\eta}_\theta = \eta_\theta$

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Outlook: Total Variation Neighborhoods

PhD project of M. Brandl; preliminary results:

- total variation $\hat{=}$ replacement outliers
 - maxMSE has a higher order expansion
 - asymmetric case
 - already in first order asymptotics different solutions for convex contamination and total variation [Ri:94]
 - asymmetric clipping for first order optimal solution [Ri:94]
 - symmetric case
 - $A_1 = 0$ — first correction term in maxMSE of order $O(n^{-1})$
 \implies faster convergence of maxMSE
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(ad Q1) no enhancement by second order asymptotics

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