# Theory for multivariate shape constraints: partial results, open problems, and conjectures

Jon A. Wellner

University of Washington

### Theory for multivariate shape constraints: -p, 1/17

- Talk at JSM, Vancouver August 1, 2010
- Email: jaw@stat.washington.edu http://www.stat.washington.edu/jaw/jaw.research.html
- Based on joint work with former Ph.D. students and postdocs: Marios Pavlides, Arseni Seregin

#### Theory for multivariate shape constraints: - p. 2/17

### Outline

- 1. Shape constraints in  $\mathbb{R}^1$  and  $\mathbb{R}^d$ : some background (and limitations).
- 2. Goals for nonparametric estimation theory
- 3. Review of results for estimating a monotone density in  $\mathbb{R}^1$
- 4. Review of recent shape-constrained estimation progress for  $\mathbb{R}^d$
- 5. Summary: available theory for  $\mathbb{R}^d$
- 6. Open problems and some conjectures

1. Shape constraints in  $\mathbb{R}^1$  and  $\mathbb{R}^d$ : background

 $\mathbb{R}^1$ : Several types of shape constraints, and several types of target functions to estimate:

- type of shape constraint:
  - monotone
  - convex (or concave)
  - *k*-monotone
  - completely monotone
  - $\circ \log$  -concave and s-concave
  - hyperbolically monotone (Bondesson)

### Theory for multivariate shape constraints: - p. 4/17

1. Shape constraints in  $\mathbb{R}^1$  and  $\mathbb{R}^d$ : background

 $\mathbb{R}^1$ : Several types of shape constraints, and several types of target functions to estimate:

- type of shape constraint:
  - monotone
  - convex (or concave)
  - *k*−monotone
  - completely monotone
  - $\circ \log$  -concave and s-concave
  - hyperbolically monotone (Bondesson)
- Type of function:
  - $\circ$  regression function r(x)
  - $\circ$  density function f(x)
  - $^{\circ}$  hazard functions,  $\lambda(x)$

Focus here on density functions — and on methods related or connected to Maximum Likelihood.

 $\mathbb{R}^d$ : More types of shape constraints, and (more?) types of target functions to estimate:

- Types of shape constraint:
  - block monotone or coordinate-wise monotone
  - monotone with non-negative increments on rectangles (as for a multivariate d.f.)
  - $^{\circ}\,$  convex (or concave) and decreasing
  - $\circ$  k-monotone; completely monotone
  - $\circ \log$  -concave and s-concave
  - $\circ$  *h*-transform of convex (or concave)

Focus here on density functions — and on methods related or connected to Maximum Likelihood.

 $\mathbb{R}^d$ : More types of shape constraints, and (more?) types of target functions to estimate:

- Types of shape constraint:
  - block monotone or coordinate-wise monotone
  - monotone with non-negative increments on rectangles (as for a multivariate d.f.)
  - $^{\circ}\,$  convex (or concave) and decreasing
  - $\circ$  k-monotone; completely monotone
  - $\circ \log$  -concave and s-concave
  - $\circ$  *h*-transform of convex (or concave)
- Types of function: regression r, density f, hazard  $\lambda \dots$

### Theory for multivariate shape constraints: - p. 5/17

## 2. Goals for limit theory

- A. Consistency (pointwise or with respect to some metric or topology)?
- B. Local (at fixed points) rates of convergence? Upper and lower bounds?
- C. Global (summary or metric) rates of convergence? Upper and lower bounds?
- D. Rates for smooth functionals: upper and lower bounds?
- E. Rates and corrections for inconsistency at boundary points?
- F. Kiefer-Wolfowitz type theorems: at what rate does the integrated version of the estimator "look like the natural empirical estimator"?

My talk today: limited to A-C.

### 3. Review for estimating a monotone density function

A. Marshall's lemma. Consistency "easy" now via Pfanzagl (1989), van de Geer (1993), and empirical process methods.  $B_L$ : Local asymptotic minimax lower bound, Groeneboom (198?):

if  $f(x_0) > 0$ ,  $f'(x_0) < 0$  and f' continuous at  $x_0$ , then for any estimator  $T_n$  of  $f(x_0)$ ,

 $\liminf_{n \to \infty} \sup_{f: H(f, f_0) \le cn^{-1/2}} n^{1/3} E_f |T_n - f(x_0)| \ge \frac{e^{-1/3}}{4} (2|f'(x_0)|f(x_0)|^{1/3}.$ 

**B**<sup>*U*</sup>: Local convergence theorem, Prakasa Rao (1970): if  $f(x_0) > 0$ ,  $f'(x_0) < 0$ , and f' is continuous at  $x_0$ , then

 $n^{1/3}(\hat{f}_n(x_0) - f(x_0)) \to_d (|f'(x_0)| f(x_0)/2)^{1/3} \mathbb{S}(0)$ 

where S(0) is the (left-)slope at zero of the least concave majorant of  $W(t) - t^2$ , and W is two-sided BM starting at 0.

C<sub>L</sub>. Birgé (1987). Let  $\mathcal{F}$  denote the class of all decreasing densities f on [0, 1] satisfying  $f \leq M$  with M > 1. Then the minimax risk for  $\mathcal{F}$  with respect to the  $L_1$  metric  $d_1(f,g) \equiv \int |f(x) - g(x)| dx$  based on n observations is

$$R_M(d_1, n) \equiv \inf_{\hat{f}_n} \sup_{f \in \mathcal{F}} E_f d_1(\hat{f}_n, f).$$

Then there is an absolute constant *C* such that

$$R_M(d_1, n) \ge C\left(\frac{\log M}{n}\right)^{1/3}$$

 $C_U$ . Birgé (1989). Let  $\hat{f}_n$  denote the Grenander estimator of  $f \in \mathcal{F}$ . Then

$$\sup_{f \in \mathcal{F}_M} E_f d_1(\hat{f}_n, f) \le 4.75 \left(\frac{\log M}{n}\right)^{1/3}$$

Theory for multivariate shape constraints: - p. 8/17

## Table 1: Montone density on $\mathbb{R}^+$

Problem	Lower Bound	Upper Bound / MLE
A (consist)		Grenander?
		Marshall? ?
		or Prakasa Rao
B (local theory)	Groeneboom (?)	Prakasa Rao (1969)
	rate: $n^{1/3}$	rate: $n^{1/3}$
	const: $( f'(x) f(x))^{1/3}$	const: $( f'(x) f(x))^{1/3}$
C (global theory)	Birgé (1987)	Birgé (1989)
	Groeneboom (1986)	

Theory for multivariate shape constraints: -p, 9/17

## 4. Shape-constrained estimation on $\mathbb{R}^d$

 "Block decreasing" densities on ℝ<sup>+d</sup> = [0,∞)<sup>d</sup> (Polonik; Biau and Devroye; Pavlides) Decreasing along along all lines parallel to coordinate axes. Can be viewed as the convex hull of densities which are uniform on (compact) lower layers:



Theory for multivariate shape constraints: -p, 10/17

 "Scale mixtures of uniform densities" on R<sup>+d</sup>: (Pavlides; Pavlides and Wellner):

$$f(\underline{x}) = \int_{\mathbb{R}^{+d}} \frac{1}{\prod_{j=1}^{d} y_j} \mathbf{1}_{[\underline{0},\underline{y}]}(\underline{x}) dG(\underline{y})$$

for some probability distribution G on  $\mathbb{R}^{+d}$ . Example:  $dG(y_1, y_2) = (y_1y_2)^{-2}g(1/y_1, 1/y_2, \theta)dy_1dy_2$  with

$$g(u, v, \theta) = \{(1+\theta u)(1+\theta v) - \theta\} \exp(-u - v - \theta uv), \qquad \theta = .4,$$



#### Theory for multivariate shape constraints: -p, 11/17

• Log-concave densities on  $\mathbb{R}^d$ (Cule, Samworth, Stewart; Koenker and Mizera; Seregin and Wellner)

$$f(\underline{x}) = \exp(\varphi(\underline{x})) = \exp(-(-\varphi(\underline{x})))$$

where  $\varphi : \mathbb{R}^d \mapsto \mathbb{R}$  is concave (so  $-\varphi$  is convex). Necessarily exponentially decaying tails; does not include multivariate *t*-densities.

 s-convex densities and h- convex densities (Koenker and Mizera; Seregin, Seregin and Wellner)

 $f(\underline{x}) = h(\varphi(\underline{x}))$ 

where  $\varphi : \mathbb{R}^d \mapsto \mathbb{R}$  is convex,  $h : \mathbb{R} \mapsto \mathbb{R}^+$  is decreasing and continuous; e.g.  $h_s(u) \equiv (1 + u/s)^{-s}$  with s > d. Larger classes than log-concave: includes multivariate  $t_n$  for  $d < s \le n + d$ .

# Table 2: Block decreasing densities on $\mathbb{R}^{+d}$

Problem	Lower Bound	Upper Bound / MLE
А		Polonik (1995,1998)
(consist)		Pavlides (2008?)
В	Pavlides (2008 & 2009)	?
(local)	rate: $n^{1/(d+2)}$	rate: $n^{1/(d+2)}$ ??
	$\left\{\prod_{j=1}^{d} \frac{\partial f}{\partial x_j}(x) f(x)\right\}^{1/(d+2)}$	const: ??
С	Biau and Devroye (2003)	Biau and Devroye (2003)
(global)	rate: $n^{1/(d+2)}$	analogues of Birgé's
		histogram estimators

### Theory for multivariate shape constraints: - p. 13/17

# Table 3: Scale mixtures of uniform on $\mathbb{R}^{+d}$

Problem	Lower Bound	Upper Bound / MLE
А		Pavlides (2008)
(consist)		Pavlides & Wellner (2010)
В	Pavlides (2008)	?
(local)	rate: $n^{1/3}$ (all $d$ )	Pavlides (2008),
	$\left\{\frac{\partial^d f}{\partial x_1 \cdots \partial x_d}(x)f(x)\right\}^{1/3}$	partial results
С	??	??
(global)	?? (hints from entropy bounds	??
	of Blei, Gao, and Li)	??

Theory for multivariate shape constraints: -p, 14/17

# Table 4: Log concave densities on $\mathbb{R}^d$

Problem	Lower Bound	Upper Bound / MLE
Α	consistency with	Cule and Samworth (2010a)
(consist)	misspecification!	Schumacher, Rufibach,
		Samworth (2010)
	computation:	Cule, Samworth, Stewart (2010)
В	Seregin (2010)	??
(local)	rate: $n^{2/(d+4)}$	??
	$\left\{f^{d+2}(x)\operatorname{curv}_x(\varphi)\right\}^{1/(d+4)}$	??
	${\sf curv}_x(arphi) = {\sf det}  abla^2 arphi(x)$	
С	??	??
(global)	conjectures:	??
	Seregin and W (2010)	??

### Theory for multivariate shape constraints: - p. 15/17

## Table 5: *s*-convex and *h*-convex densities on $\mathbb{R}^d$

Problem	Lower Bound	Upper Bound / MLE
А		Seregin & W (2010)
(consist)	computation:	
	(related estimators)	Koenker & Mizera (2010)
	(convex regression)	Seijo and Sen (2010)
В	Seregin (2010)	?? LSE rate inefficient
(local)	rate: $n^{2/(d+4)}$	<i>d</i> > 4 <b>??</b>
	$\left\{\frac{f(x)CUrv_x(\varphi)}{h'(\varphi(x))^4}\right\}^{1/(d+4)}$	??
С	??	?? LSE rate inefficient,
(global)	??	d > 4??
	??	or $d \geq 4$ ??

Theory for multivariate shape constraints: - p. 16/17

## 5. Open problems and some conjectures

- local rates and global rates for shape constrained estimators in  $\mathbb{R}^d$ ?
- Local (pointwise) limiting distribution theory for MLE's and other natural divergence-based estimators?
- When are the MLE's rate (in-)efficient?
   Conjecture 1: Block decreasing: inefficient for d > 2.
   Conjecture 2: Log-concave and s-concave: inefficient for d > 4.
- Do there exist natural shape-constraints with smoothness
   2 for which MLE's are rate-efficient and which have
   natural preservations properties under convolution,
   marginalization, and so forth?

   Conjecture 3: Yes for d = 1 via the hyperbolic k-monotone
   classes of Bondesson?