Quasi-Concave Density Estimation

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Joint work with Ivan Mizera, University of Alberta

Regularization for Density Estimation

Maximum likelihood estimation of densities

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Dirac Catastrophe

Cai Guo-Qiang's "Transient Rainbow" New York, 2002

Regularization – Remedies for Ill-Posedness

Two general classes of treatments:

- Norm Constraints: $\max_{f \in \mathcal{F}} \sum_{i=1}^{n} \log f(X_i) - \lambda \|D^k h(f)\|$
  - Good (1971) $\|D\sqrt{f}\|_2^2$
  - Silverman (1982) $\|D^3 \log(f)\|_2^2$
  - Wahba/Gu (2002) $\|D^2 \log(f)\|_2^2$
  - Davies/Kovac (2004) $TV(f) = \|Df\|_1$
  - Koenker/Mizera (2005) $TV((\log f)') = \|D^2 \log f\|_1$

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  - Davies/Kovac (2004) $TV(f) = \|Df\|_1$
  - Koenker/Mizera (2005) $TV((\log f)') = \|D^2 \log f\|_1$
- Shape Constraints: $\max_{f \in \mathcal{F}} \{\sum_{i=1}^{n} \log f(X_i) | D^k h(f) \in \mathcal{K}\}$
  - Grenander (1956) f monotone
  - Rufibach/Dümbgen (2006) $\log f$ concave
  - Cule, Samworth, Stewart (2006) $\log f$ concave

On Tautology: The New, Improved Histogram

The simplest example of a total variation penalized density estimator is the tautstring estimator of Hartigan and Hartigan (1985) elaborated by Davies and Kovac (2001, 2004) and van de Geer and Mammen (1997).

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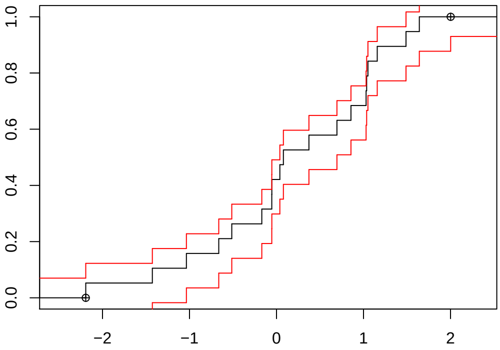
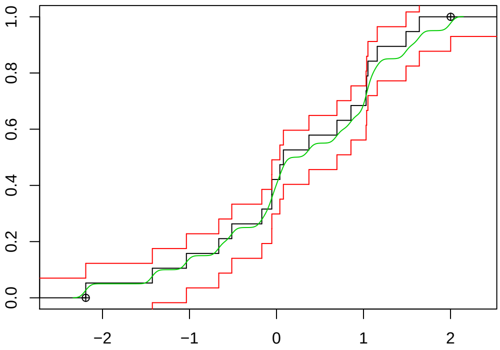
- Make a $\pm\epsilon$ Kolmogorov tube around the empirical df.
- Attach a string to the points $(X_{(1)}, 0)$ and $(X_{(n)}, 1)$.
- Pull the string taut.

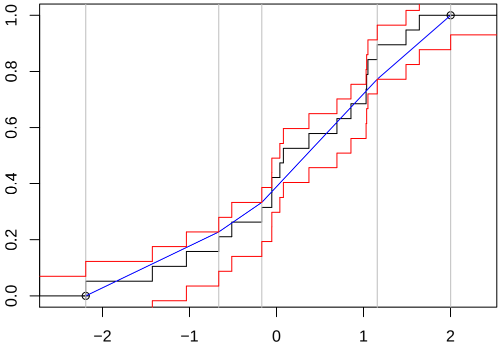
The Kolmogorov Tube



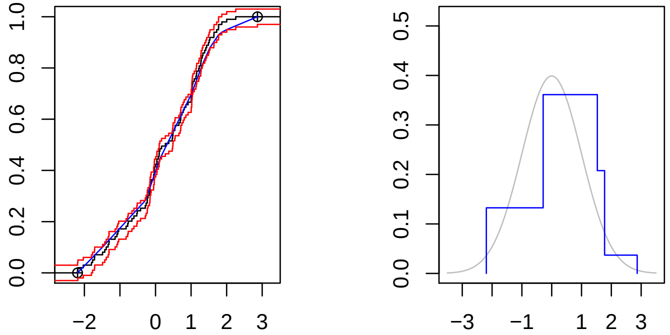
The Slack String



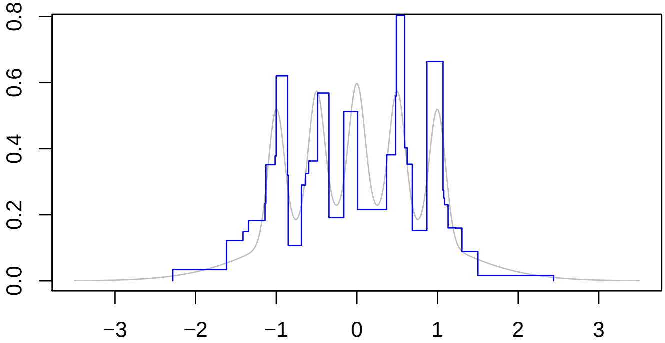
The Taut String



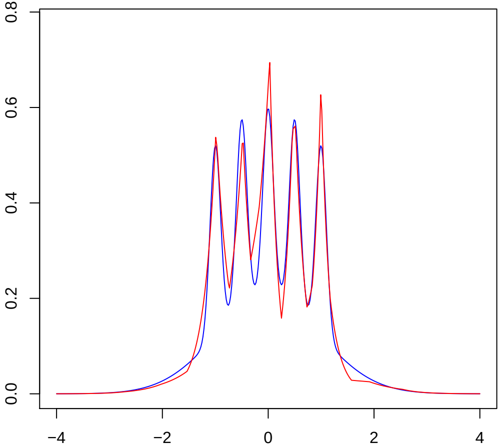
Taut String Densities are Piecewise Constant



And Good at Estimating Modality



MLE's using TV Penalties on $(\log f)'$ Are Even Better



Shape Constrained Density Estimation: Early History

Grenander (1956) considered the maximum likelihood estimation of a monotone density:

$$\max\{\sum \log f(X_i) \mid f \searrow, \int f dx = 1\}$$

Solutions are piecewise constant functions with jumps at the observed $\{X_i\}$; they are derivatives of the least concave majorant, of the empirical distribution function, F_n.

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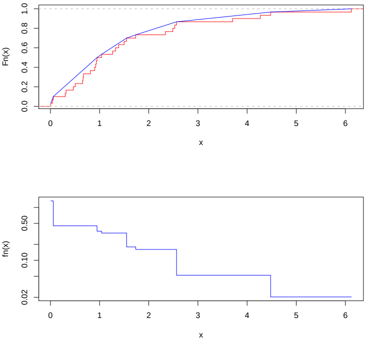

Grenander in Asymptopia

What do we know about the asymptotic behavior of Grenander's f_n?
There is a large literature: Prakasa Rao (1969), Groeneboom (1985), ...

Prop 1 If a monotone density f is differentiable and strictly decreasing at a point, x, then,

$$n^{1/3}(\hat{f}_n(x) - f(x)) \rightsquigarrow |4f'(x)f(x)|^{1/3} \text{argmax}\{\mathbb{Z}(h) - h^2\}$$

where $\{\mathbb{Z}(h) : h \in \mathbb{R}\}$ is a standard Brownian motion with $\mathbb{Z}(0) = 0$.

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Prop 2 If f is strictly monotone decreasing and twice differentiable, then

$$n^{1/3} \int |\hat{f}_n(x) - f(x)| dx \rightsquigarrow \int |4f'(x)f(x)|^{1/3} dx \; \mathbb{E} \, \text{argmax}\{\mathbb{Z}(h) - h^2\}.$$

From Monotone to Unimodal Densities

If f is unimodal with a known mode then we can employ Grenander on each side of the mode to the same effect. Estimation of the mode can also be done so that the same rate is achievable with an estimated mode. Birgé (1997).

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But unimodal densities aren't quite as appealing as they might at first appear. A more attractive class consists of strongly unimodal, or log-concave densities.

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What's so great about log-concave densities?

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- Many common densities are log concave: uniform, Gaussian, Laplacian, some Gammas, some Weibulls, ...
- Numerous applications in virtually every corner of economic theory: search, signaling, reliability, auction design, pricing in differentiated product markets, and social choice all rely on log concavity conditions.

Beyond the Log Concave Horizon

Following Hardy, Littlewood and Polya (1934), recall that means of order ρ are defined as

$$M_\rho(a;p) = M_\rho(a_1, ..., a_n; p) = (\sum p_i a_i^\rho)^{1/\rho}$$

for p in the unit simplex, $\mathcal{S} = \{p \in \mathbb{R}^n_+ | \sum p_i = 1\}$.

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Examples: The classical means:

- $\rho = 1$ Arithmetic,
- $\rho = 0$ Geometric,
- $\rho = -1$ Harmonic.

Beyond the Log Concave Horizon

Definition (Avriel (1972)) A non-negative real function g defined on a convex set $C \subset \mathbb{R}^d$, is ρ-concave if for any $x_0, x \in C$ and $p \in \mathcal{S}$,

$$g(p_0 x_0 + p_1 x_1) \geqslant M_\rho(g(x_0), g(x_1); p).$$

Note that

- concave functions are 1-concave,
- log-concave functions are 0-concave, ...
- σ-concaves are ρ-concave for all $\sigma > \rho$.
- $-\infty$-concaves are quasi-concave.

Moral: Some concaves are more concave than other concaves, but all are quasi-concave, that is they have convex level sets.

An Application to Voting and Social Choice

Caplin and Nalebuff (1992) consider a spatial model of voting in which agents have preferred positions in "issue space" according a ρ-concave density $f : \mathbb{R}^d \to \mathbb{R}$.

It is then demonstrated that the mean voter's preferred position is preferred by at least a proportion $1 - \delta$ of voters to any other proposed position, where

$$\delta(d, \rho) = 1 - \left[\frac{d + 1/\rho}{d + 1 + 1/\rho} \right]^{d+1/\rho}.$$

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This generalizes the celebrated Black (1948) median voter result for (weakly) unimodal densities.

Nonparametric Maximum Likelihood

We can easily pose the problem:

$$\max_f \{\prod_{i=1}^{n} f(X_i) \mid f \text{ is a log-concave density}\}$$

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What about dimension $d > 1$? Koenker and Mizera (2008) suggest interior point methods, while Cule, Samworth and Stewart (2007) explore gradient methods.

A Characterization Lemma

Solutions to (P) are polyhedral convex functions of the form

$$\hat{g}(x) = \inf\left\{\sum_{i=1}^{n} \lambda_i Y_i \mid x = \sum_{i=1}^{n} \lambda_i X_i, \sum_{i=1}^{n} \lambda_i = 1, \lambda_i \geqslant 0\right\},$$

where $\{X_i\}$ are the sample observations and the Y_i are freely varying, representing ordinates of the estimated density at the X_i's.

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Implications:

- Reduces the problem to a finite, albeit n-dimensional, one.
- Solution log-densities are piecewise linear, i.e. polyhedral..
- Solution densities are piecewise exponential.
- Estimated densities vanish off the convex hull of the observations.

A Family of Convex Variational Problems

A functional version of our MLE problem (P) can be written as

$$\min_g \{ \int g dP_n + \int e^{-g} dx \mid g \in \mathcal{K} \}$$

where $\mathcal{K}$ denotes the cone of convex functions on $\mathcal{C}(X)$, the linear space of all bounded continuous functions on $\mathcal{H}(X)$, the convex hull of the $\{X_i\}$.

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It is useful to expand somewhat the class of these problems beyond the MLE log concave case, so we will rewrite this as,

$$\min_g \{ \int g dP_n + \int \psi(g) dx \mid g \in \mathcal{K} \}$$

Through the Looking Glass, Dually

Theorem Suppose that ψ is a decreasing convex function of a real variable with conjugate (Legendre transform) $\psi^*(y) = \sup_x\{yx - \psi(x)\}$, then the strong dual of the primal problem

$$(P) \qquad \min_g \{\int g dP_n + \int \psi(g) dx \mid g \in \mathcal{K}\}$$

is given by:

$$(D) \qquad \max_G \{-\int \psi^*(-f) dx \mid f = \frac{d(P_n - G)}{dx},\ G \in \mathcal{K}^*\}$$

where $\mathcal{K}^* = \{G \in \mathcal{C}^*(X) \mid \int g dG \geqslant 0 \text{ for all } g \in \mathcal{K}\}$, and $\mathcal{C}^*(X)$ is the space of signed Radon measures on $\mathcal{H}(X)$, the set of bounded, continuous functions on X. Note that G must anihilate the atoms of P_n so that f is a (Lebesgue) density.

Dual Exhausts

Thus, for the original MLE log-concave example: $\psi(x) = e^{-x}$ we have $\psi^*(y) = -y\log(-y) + y$ giving the dual problem,

$$\max_f \{-\int f\log(f)dx \mid f = \frac{d(P_n - G)}{dx}, G \in \mathcal{K}^*\}$$

So the MLE problem becomes a maximum Shannon entropy problem.

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The usual suspects (shades of Cressie-Read and Csiszár divergences):

- $\alpha = 1$ is Shannon (taking limits)
- $\alpha = 2$ is Pearson χ^2
- $\alpha = 1/2$ is Hellinger
- $\alpha = 0$ is (some form of) Empirical Likelihood

Don Juan in Hellinger

Our favorite alternative to Shannon is $\alpha = 1/2$,

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- All Student's are admitted up to and including Cauchy.
- These are Avriel's ρ-concaves, with $\rho = \alpha - 1 = -1/2$.
- Recall that this class nests the log-concaves.

Inference about Log Concave Mixtures

Another interesting class of densities is mixtures of log-concaves.

Theorem (Walther (2002)) Let $\{f_i\}$ be a collection of log-concave densities on $\mathbb{R}^d$, then on any compact set $G \subset \bigcap \text{supp}\{f_i\}$ we have the following representation for the mixture density:

$$f(x) \equiv \sum p_i f_i(x) = \exp\{\phi(x) + c\|x\|^2\}$$

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Leads to interesting tests for $H_0 : c = 0$: Log-concavity vs everything else.

An Identifiability Dilemma

The downside of the Walther result is that non-parametric identifiability of mixtures is thrown into a rather perilous swamp: we can reproduce any mixture of log-concaves by simply introducing a little convexity into the exponential family representation of a single log-concave:

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Moral: Distributions are from God, parameterizations are from man.

Algorithms and Actuality

Discrete implementations require two basic ingredients:

- Data: $\{X_1, \cdots, X_n\}$
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- $\int \psi(g)dx \approx \sum s_i \psi(g(v_i)) \equiv s^\top \Psi(\gamma)$ Riemann Sum
- $\int g dP_n = \sum g(X_i) = w^\top L\gamma$ Linear Interpolation
- $g \in \mathcal{K} \Leftrightarrow D\gamma \geqslant 0 \quad D = \nabla^2$ Convex Cone Constraint

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We parameterize $g = (g(v_i))_{i=1}^m \equiv (\gamma_i)_{i=1}^m$, thus:

- $\int \psi(g)dx \approx \sum s_i \psi(g(v_i)) \equiv s^\top \Psi(\gamma)$ Riemann Sum
- $\int g dP_n = \sum g(X_i) = w^\top L\gamma$ Linear Interpolation
- $g \in \mathcal{K} \Leftrightarrow D\gamma \geqslant 0 \quad D = \nabla^2$ Convex Cone Constraint

Yielding the primal and dual problems:

$$(P) \qquad \{w^\top L\gamma + s^\top \Psi(\gamma) \mid D\gamma \geqslant 0\} = \min!$$

$$(D) \qquad \{-s^\top \Psi^*(f) \mid Sf = w^\top L + D^\top h, f \geqslant 0, D^\top h \geqslant 0\} = \max!$$

The Discrete Charm of Duality

$$\text{(P)} \qquad \{w^\top L\gamma + s^\top \Psi(\gamma) \mid D\gamma \geqslant 0\} = \min!$$

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Theorem: (Sanity Check) In (P) suppose that for a vector of ones, ι, $w^\top L\iota = 1$ and $D\iota = 0$, then solutions f and g are strongly dual and satisfy:

$$f(v_i) = \psi'(g(v_i)) \quad i = 1, \cdots, m,$$

and $\int f(x)dx = \sum s_i f(v_i) = 1$, and $f(v_i) \geqslant 0$.

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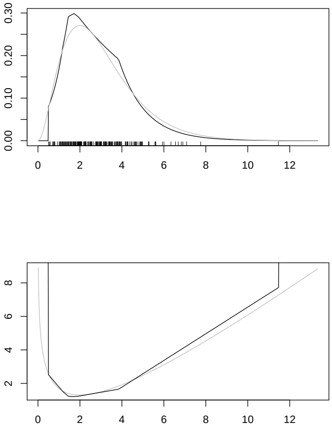
The argument for the integrability constraint is especially simple and revealing:

$$s^\top f \equiv \iota^\top Sf = \iota^\top Lw + \iota^\top D^\top h = 1$$

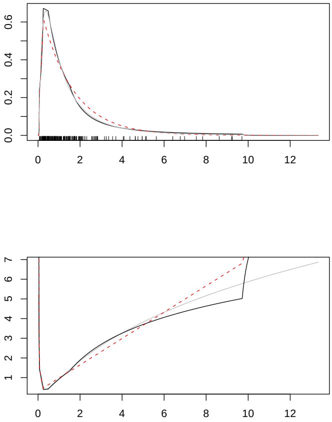
Since $D = \nabla^2$ the same argument implies that $\int xf(x)dx = \int xdP_n$.

A Gamma Example



Log-concave Maximum Likelihood Estimator of a Gamma(3) Density

A Log-Normal Example



Log-concave and -1/2-concave Estimates of a Log-Normal Density

An Historical Bivariate Example

"Student" (W.S. Gosset) in his celebrated 1908 paper writes:

> *Before I had succeeded in solving my problem analytically, I had endeavoured to do so empirically. The material used was a correlation table containing the height and left middle finger measurements of 3000 criminals, from a paper by W. R. Macdonell. The measuremensts were written out on 3000 pieces of cardboard, which were then very thoroughly shuffled and drawn at random. Finally each consecutive set of 4 was taken as a sample . . .*

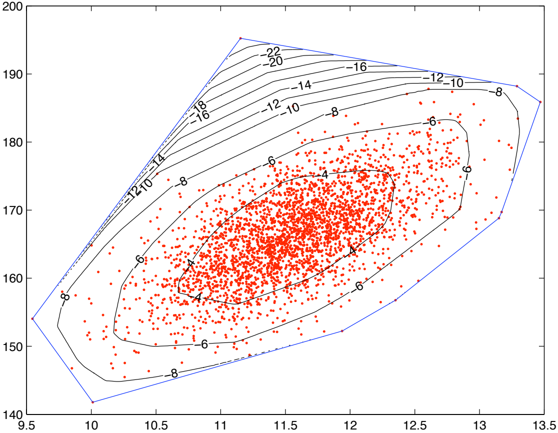
216 *On Criminal Anthropometry*

TABLE III. 3000 *Criminals.* Height (feet and inches).

Left Middle Finger (millimetres).

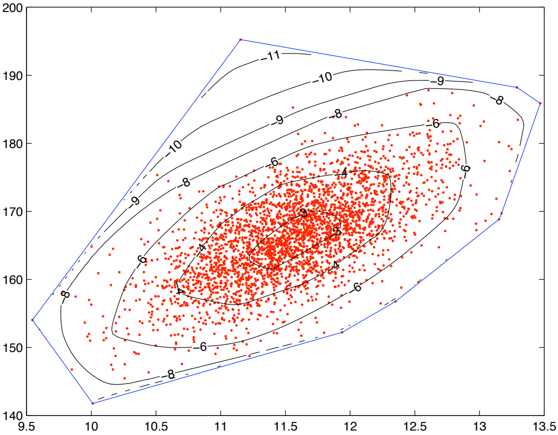
	4′ 7″ 9/16–8″ 9/16	8″ 9/16–9″ 9/16	9″ 9/16–10″ 9/16	10″ 9/16–11″ 9/16	5′ 11″ 9/16–0″ 9/16	0″ 9/16–1″ 9/16	1″ 9/16–2″ 9/16	2″ 9/16–3″ 9/16	3″ 9/16–4″ 9/16	4″ 9/16–5″ 9/16	5″ 9/16–6″ 9/16	6″ 9/16–7″ 9/16	7″ 9/16–8″ 9/16	8″ 9/16–9″ 9/16	9″ 9/16–10″ 9/16	10″ 9/16–11″ 9/16	6′ 11″ 9/16–0″ 9/16	0″ 9/16–1″ 9/16	1″ 9/16–2″ 9/16	2″ 9/16–3″ 9/16	3″ 9/16–4″ 9/16	4″ 9/16–5″ 9/16	Totals
9·4	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
5	—	—	—	—	—	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1
6	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0
7	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0
8	—	—	—	—	—	—	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1
9	—	—	1	—	1	—	1	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	3
10·0	1	—	—	1	2	—	2	—	—	1	—	—	—	—	—	—	—	—	—	—	—	—	7
1	—	—	—	1	3	1	—	1	1	—	—	—	—	—	—	—	—	—	—	—	—	—	7
2	—	—	2	2	2	1	—	2	—	1	—	—	—	—	—	—	—	—	—	—	—	—	10
3	—	1	1	3	2	2	3	5	—	—	—	—	—	—	—	—	—	—	—	—	—	—	17
4	—	—	1	1	2	3	3	4	3	3	—	—	—	—	—	—	—	—	—	—	—	—	20
5	—	—	—	1	3	7	6	4	3	1	3	1	—	1	—	—	—	—	—	—	—	—	30
6	—	—	—	1	4	5	9	14	6	3	1	—	—	1	—	—	—	—	—	—	—	—	44
7	—	—	1	2	4	9	14	16	15	7	3	1	2	—	—	—	—	—	—	—	—	—	74
8	—	—	—	2	5	6	14	27	10	7	1	2	1	—	—	—	—	—	—	—	—	—	75
9	—	—	—	—	2	6	14	24	27	14	10	4	1	—	—	—	—	—	—	—	—	—	102
11·0	—	—	—	2	6	12	15	31	37	27	17	10	6	—	—	—	—	—	—	—	—	—	163
1	—	—	—	3	3	12	22	26	24	26	24	7	4	1	—	—	—	—	—	—	—	—	152
2	—	—	—	3	2	7	21	30	38	29	27	20	4	1	—	—	—	—	—	—	—	1	183
3	—	—	—	1	—	5	10	24	26	39	26	24	7	2	—	—	—	—	—	—	—	—	164
4	—	—	—	—	3	4	9	29	56	58	26	22	10	11	—	—	—	—	—	—	—	—	228
5	—	—	—	—	—	5	11	17	33	57	38	34	25	11	2	—	—	—	—	—	—	—	233
6	—	—	—	—	2	1	4	13	37	39	48	38	27	12	2	2	—	1	—	—	—	—	226
7	—	—	—	—	—	2	9	17	30	37	48	45	24	9	9	2	—	—	—	—	—	—	232
8	—	—	—	—	1	—	2	11	15	35	41	34	29	10	5	1	—	—	—	—	—	—	184
9	—	—	—	—	1	1	2	12	10	27	32	35	19	10	9	3	1	—	—	—	—	—	162
12·0	—	—	—	—	—	—	1	4	8	19	42	39	22	16	8	2	2	—	—	—	—	—	163
1	—	—	—	—	—	—	—	2	4	13	22	28	15	27	10	4	1	—	—	—	—	—	126
2	—	—	—	—	—	—	1	2	5	6	23	17	16	11	8	1	1	—	—	—	—	—	91
3	—	—	—	—	—	—	—	—	4	8	10	13	20	23	6	5	—	—	—	—	—	—	89
4	—	—	—	—	—	—	1	1	1	2	7	12	4	7	7	1	—	—	1	—	—	—	44
5	—	—	—	—	—	—	—	1	—	1	3	12	11	8	6	8	—	2	—	—	—	—	52
6	—	—	—	—	—	—	—	—	—	1	—	3	5	7	8	6	3	1	1	—	—	—	35
7	—	—	—	—	—	—	—	—	—	1	1	7	5	5	8	2	2	—	—	—	—	—	31
8	—	—	—	—	—	—	—	—	—	—	1	2	3	1	8	5	3	1	1	—	—	—	25
9	—	—	—	—	—	—	—	—	—	—	—	1	2	2	—	1	1	—	—	—	—	—	7
13·0	—	—	—	—	—	—	—	—	—	—	3	—	1	—	1	—	2	1	—	—	—	—	8
1	—	—	—	—	—	—	—	—	—	—	—	1	1	—	—	—	—	—	—	—	—	—	2
2	—	—	—	—	—	—	—	—	—	—	1	1	—	1	—	3	—	—	—	—	—	—	6
3	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1	—	1	—	—	—	2
4	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	0
5	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	1	—	—	—	—	1
Totals	1	1	6	23	48	90	175	317	393	462	458	413	264	177	97	46	17	7	4	0	0	1	3000
Means	100	103	102·6	107·0	107·8	109·4	110·6	111·8	115·3	114·8	116·5	117·7	118·6	120·1	122·2	123·9	125·9	126·4	127·7	—	—	112	

Student's Middle Fingers



Bivariate Log-Concave Estimate

Student's Middle Fingers, Again



Bivariate −1/2-Concave Hellinger Estimate

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- Why density estimation? Because it is a stepping stone toward the hegemony of semi-parametrics.