

Active Set Methods for Log-Concave Densities and Nonparametric Tail Inflation

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The general setting

Data. Summarized as a distribution

$$\hat{P} = \sum_{i=1}^n w_i \delta_{x_i}$$

with

- ▶ weights $w_1, w_2, \dots, w_n > 0$
- ▶ support points $x_1 < x_2 < \dots < x_n$ in an open interval $\mathcal{X} \subset \mathbb{R}$

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Model. \hat{P} estimates distribution

$$P(dx) = e^{\theta(x)} M(dx)$$

with

- ▶ given measure M on \mathcal{X}
- ▶ unknown function θ in given family Θ_1

Goal. Estimate $\theta \in \Theta_1$ via MLE

$$\hat{\theta} \in \arg \max_{\theta \in \Theta_1} \int \theta d\hat{P}$$

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Modification. Suppose that for a larger function family Θ

$$\Theta_1 = \left\{ \theta \in \Theta : \int e^\theta dM = 1 \right\}$$

$$\theta + c \in \Theta \quad \text{for all } \theta \in \Theta, c \in \mathbb{R}$$

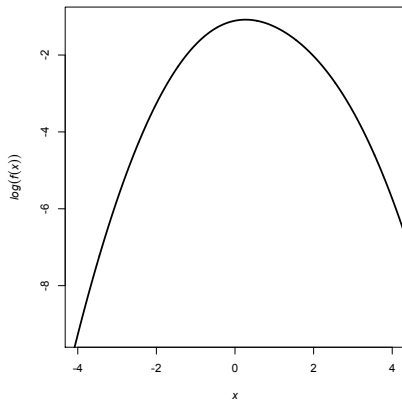
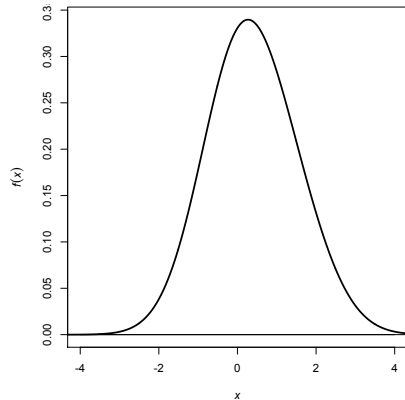
Then

$$\hat{\theta} \in \arg \max_{\theta \in \Theta} \left(\int \theta d\hat{P} - \int e^\theta dM \right)$$

Setting 1: Log-concave densities

P has **log-concave** density on \mathcal{X} , i.e.

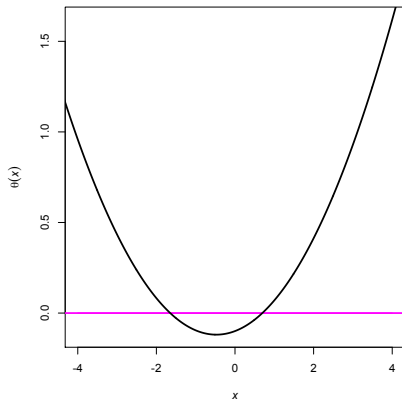
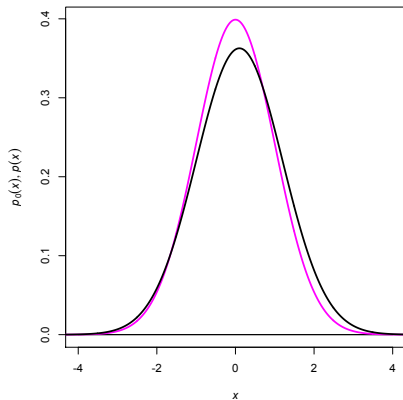
- ▶ $M =$ Lebesgue measure on \mathcal{X}
- ▶ $\Theta = \{\theta : \mathcal{X} \rightarrow [-\infty, \infty) \text{ concave and u.s.c.}\}$



Setting 2A: Tail inflation

P has **log-convex** density w.r.t. given distribution P_0 on \mathcal{X} , i.e.

- ▶ $M = P_0$
- ▶ $\Theta = \{\theta : \mathcal{X} \rightarrow \mathbb{R} \text{ convex}\}$



Example. Observe

$$X_i = \mu_i + \sigma_i \varepsilon_i, \quad 1 \leq i \leq n,$$

with unknown parameters $\mu_i \in \mathbb{R}$, $\sigma_i \geq 1$ and independent r.v.s

$$\varepsilon_i \sim P_0 := \mathcal{N}(0, 1)$$

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$$\varepsilon_i \sim P_0 := \mathcal{N}(0, 1)$$

Marginal dist. $P := n^{-1} \sum_{i=1}^n \mathcal{L}(X_i)$:

$$\theta(x) := \log \frac{dP}{dP_0}(x) = \log \left(\frac{1}{n} \sum_{i=1}^n e^{\theta_i(x)} \right)$$

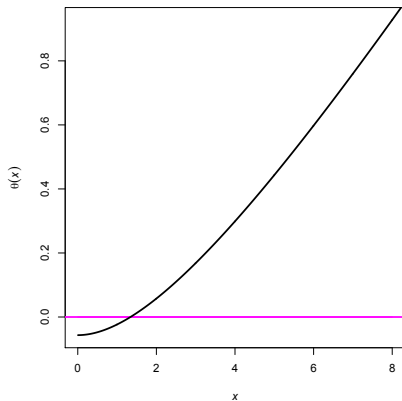
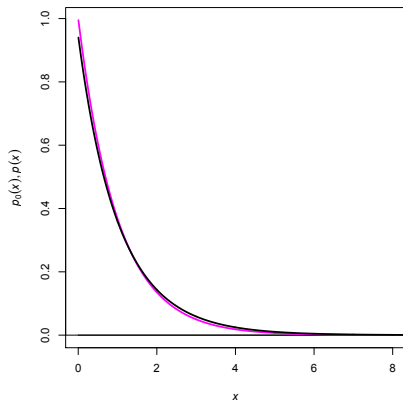
$$\theta_i(x) := -\log(\sigma_i) + \frac{x^2}{2} - \frac{(x - \mu_i)^2}{2\sigma_i^2}$$

$$\theta_i'', \theta'' \geq 0 \quad (\text{Artin's theorem})$$

Setting 2B: Tail inflation (McCullagh and Polson 2012)

Assume that P has **log-convex** and **isotonic** density w.r.t. given distribution P_0 on \mathcal{X} , i.e.

- ▶ $M = P_0$
- ▶ $\Theta = \{\theta : \mathcal{X} \rightarrow \mathbb{R} \text{ convex and isotonic}\}$.



Example. Observe

$$X_i = S_i \varepsilon_i, \quad 1 \leq i \leq n,$$

with independent r.v.s

$$\varepsilon_i \sim \mathcal{N}(0, 1), \quad S_i \geq 1.$$

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Then

$$Y_i := X_i^2 \sim \begin{cases} P_0 = \chi_1^2 = \text{Gamma}(1/2, 2) & \text{if } S_i \equiv 1 \\ \text{IE Gamma}(1/2, 2S_i^2) & \text{in general} \end{cases}$$

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Marginal dist. $P := n^{-1} \sum_{i=1} \mathcal{L}(Y_i)$:

$$\theta := \log \frac{dP}{dP_0} \text{ is convex and isotonic}$$

Existence and uniqueness of $\hat{\theta}$

Lemma 1 (Log-concavity) In Setting 1,

$$\exists! \hat{\theta} \in \arg \max_{\theta \in \Theta} \left(\int \theta d\hat{P} - \int_{\mathcal{X}} e^{\theta(x)} dx \right).$$

Existence and uniqueness of $\hat{\theta}$

Lemma 1 (Log-concavity) In Setting 1,

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Additional properties:

- ▶ $\hat{\theta}$ piecewise linear on $[x_1, x_n]$
- ▶ changes of slope only in $\{x_2, \dots, x_{n-1}\}$
- ▶ $\hat{\theta} \equiv -\infty$ on $\mathbb{R} \setminus [x_1, x_n]$

Lemma 2. In Settings 2A and 2B,

$$\exists! \hat{\theta} \in \arg \max_{\theta \in \Theta} \left(\int \theta d\hat{P} - \int e^{\theta} dP_0 \right)$$

provided that $\text{supp}(P_0) = \mathcal{X}$.

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Additional properties:

- ▶ $\hat{\theta}$ piecewise linear on \mathcal{X}
- ▶ changes of slope only in $\bigcup_{i=1}^{n-1} (x_i, x_{i+1})$
- ▶ at most one change of slope in (x_i, x_{i+1}) , $1 \leq i < n$

Active set algorithm

In Settings 1 and 2A,

$$\hat{\theta} \in \mathbb{V} \cap \Theta$$

with

$$\mathbb{V} := \{\text{linear splines on } \mathcal{X}_o \text{ with kinks on } \mathcal{D}\}$$

$$\mathcal{X}_o := \begin{cases} [x_1, x_n] & \text{in Setting 1} \\ \mathcal{X} & \text{in Setting 2A} \end{cases}$$

$$\mathcal{D} := \begin{cases} \{x_2, \dots, x_{n-1}\} & \text{in Setting 1} \\ \mathcal{X} & \text{in Setting 2A} \end{cases}$$

For such a spline $v \in \mathbb{V}$ set

$$D(v) := \{\tau \in \mathcal{D} : v'(\tau -) \neq v'(\tau +)\}$$

(deactivated (equality) constraints)

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For finite set $D \subset \mathcal{D}$ define

$$\mathbb{V}_D := \{v \in \mathbb{V} : D(v) \subset D\}$$

a linear space with

$$\dim(\mathbb{V}_D) = 2 + \#D$$

Target functional

$$L(\theta) := \int \theta d\hat{P} - \int e^\theta dM$$

with directional derivatives

$$DL(\theta, v) := \lim_{t \rightarrow 0^+} \frac{L(\theta + tv) - L(\theta)}{t}$$

Target functional

$$L(\theta) := \int \theta d\hat{P} - \int e^\theta dM$$

with directional derivatives

$$DL(\theta, \nu) := \lim_{t \rightarrow 0^+} \frac{L(\theta + t\nu) - L(\theta)}{t}$$

Characterization of $\hat{\theta}$. $\theta \in \mathbb{V} \cap \Theta$ equals $\hat{\theta}$ if, and only if,

$$DL(\theta, \nu) \leq 0 \quad \text{whenever } \theta + t\nu \in \Theta \text{ for some } t > 0.$$

Local Search (Shape-constrained Newton). Let $\theta \in \mathbb{V} \cap \Theta$.

```
 $\theta_{\text{new}} \leftarrow \text{Newton}(\theta, \mathbb{V}_{D(\theta)})$ 
```

```
 $\delta \leftarrow DL(\theta, \theta_{\text{new}} - \theta)$ 
```

```
while  $\delta > \delta_o$  do
```

```
  while  $L(\theta_{\text{new}}) < L(\theta) + \delta/3$  do
```

```
     $\theta_{\text{new}} \leftarrow (\theta + \theta_{\text{new}})/2$ 
```

```
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```

```
  end while
```

```
  if  $\theta_{\text{new}} \notin \Theta$  do
```

```
     $t_o \leftarrow \max\{t \in (0, 1] : (1 - t)\theta + t\theta_{\text{new}} \in \Theta\}$ 
```

```
     $\theta_{\text{new}} \leftarrow (1 - t_o)\theta + t_o\theta_{\text{new}}$ 
```

```
  end if
```

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   $\theta \leftarrow \theta_{\text{new}}$ 
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   $\theta_{\text{new}} \leftarrow \text{Newton}(\theta, \mathbb{V}_{D(\theta)})$ 
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   $\delta \leftarrow DL(\theta, \theta_{\text{new}} - \theta)$ 
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```
end while
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Essential properties of local search:

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- ▶ $L(\theta)$ increases
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- ▶ $L(\theta)$ increases
- ▶ $D(\theta)$ decreases
- ▶ Eventually, θ is locally optimal (approx.):

$$\theta = \arg \max_{\eta \in \mathbb{V}_{D(\theta)}} L(\eta)$$

Checking optimality. Let $\theta \in \mathbb{V} \cap \Theta$ be locally optimal (approx.).

Then

$$\theta = \hat{\theta}$$

if, and only if,

$$DL(\theta, V_\tau) \leq 0 \quad \text{for all } \tau \in \mathcal{D} \setminus D(\theta)$$

where

$$V_\tau(x) := \begin{cases} -(x - \tau)^+ & \text{in Setting 1} \\ +(x - \tau)^+ & \text{in Setting 2A} \end{cases}$$

Checking optimality. Let $\theta \in \mathbb{V} \cap \Theta$ be locally optimal (approx.).

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$$V_\tau(x) := \begin{cases} -(x - \tau)^+ & \text{in Setting 1} \\ +(x - \tau)^+ & \text{in Setting 2A} \end{cases}$$

If not, determine $\tau(\theta) \in \mathcal{D} \setminus D(\theta)$ such that

$$0 < DL(\theta, V_{\tau(\theta)}) \approx \max_{\tau \in \mathcal{D} \setminus D(\theta)} DL(\theta, V_\tau)$$

and run a **modified local search**.

Modified local search.

```
 $\theta_{\text{new}} \leftarrow \text{Newton}(\theta, \nabla_{D(\theta) \cup \{\tau(\theta)\}})$   
 $\delta \leftarrow DL(\theta, \theta_{\text{new}} - \theta)$   
while  $\delta > \delta_o$  do  
  while  $L(\theta_{\text{new}}) < L(\theta) + \delta/3$  do  
     $\theta_{\text{new}} \leftarrow (\theta + \theta_{\text{new}})/2$   
     $\delta \leftarrow \delta/2$   
  end while  
  if  $\theta_{\text{new}} \notin \Theta$  do  
     $t_o \leftarrow \max\{t \in (0, 1] : (1-t)\theta + t\theta_{\text{new}} \in \Theta\}$   
     $\theta_{\text{new}} \leftarrow (1-t_o)\theta + t_o\theta_{\text{new}}$   
  end if  
   $\theta \leftarrow \theta_{\text{new}}$   
   $\theta_{\text{new}} \leftarrow \text{Newton}(\theta, \nabla_{D(\theta)})$   
   $\delta \leftarrow DL(\theta, \theta_{\text{new}} - \theta)$   
end while
```

Remarks.

- ▶ After finitely many (modified) local searches algorithm will stop at $\theta = \hat{\theta}$ (approx.)

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- ▶ Replace simple kink functions $V_\tau = \pm(\cdot - \tau)^+$ with 'localized versions' to gain numerical precision

Remarks.

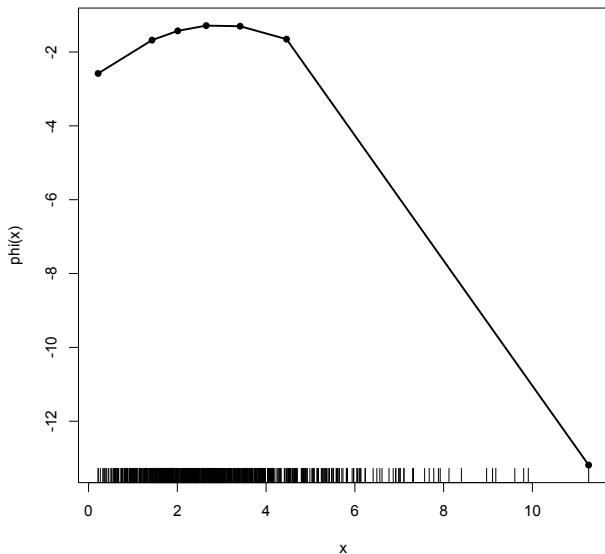
- ▶ After finitely many (modified) local searches algorithm will stop at $\theta = \hat{\theta}$ (approx.)
- ▶ Replace simple kink functions $V_\tau = \pm(\cdot - \tau)^+$ with 'localized versions' to gain numerical precision
- ▶ In Settings 2A and 2B, the function

$$\tau \mapsto DL(\theta, V_\tau)$$

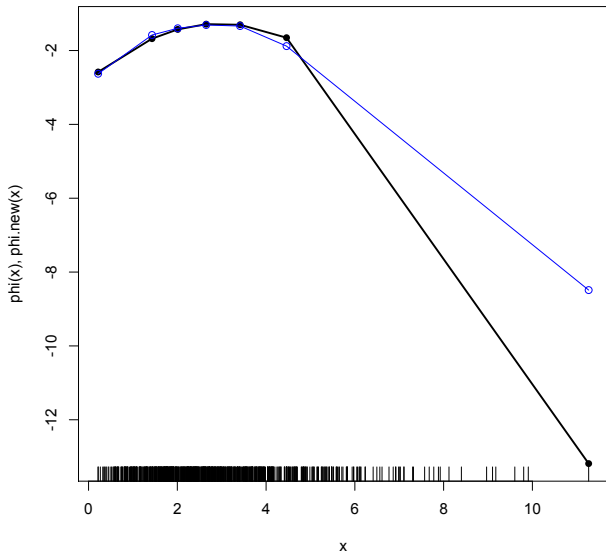
is strictly concave on any interval $(x_i, x_{i+1}) \dots$

Example for Setting 1. $n = 800$ observations from $\text{Gamma}(3, 1)$

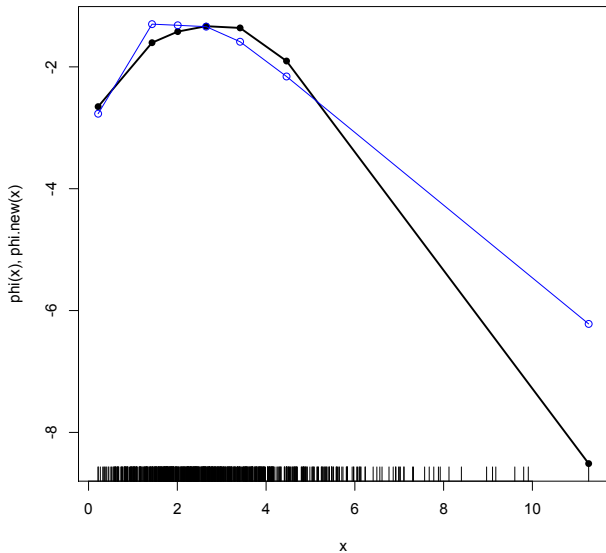
Starting point: LL = -1.953746229



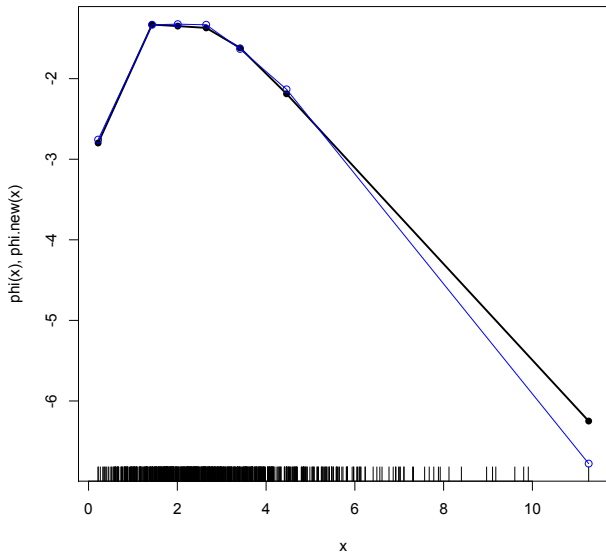
LL = -1.953746229 , dir. deriv. = 0.1233487665



LL = -1.854227796 , dir. deriv. = 0.0500846612

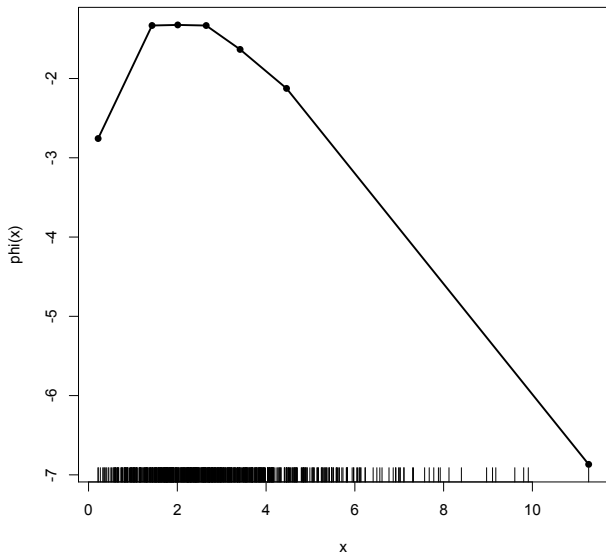


LL = -1.834138163 , dir. deriv. = 0.0042496403

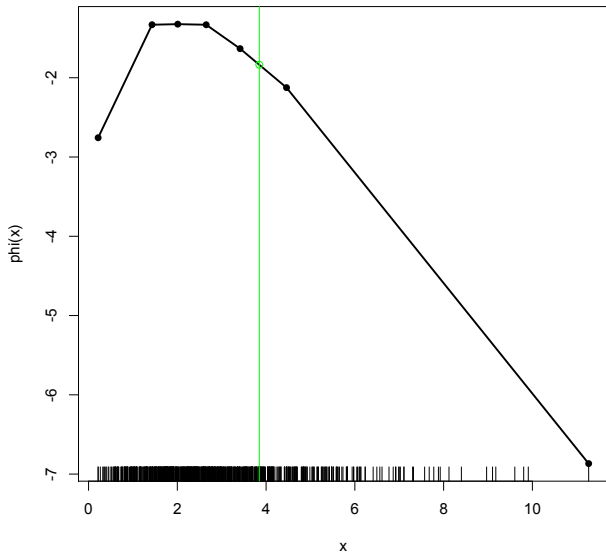


Newton proposals in dimensions 7,7,7,7,7,7

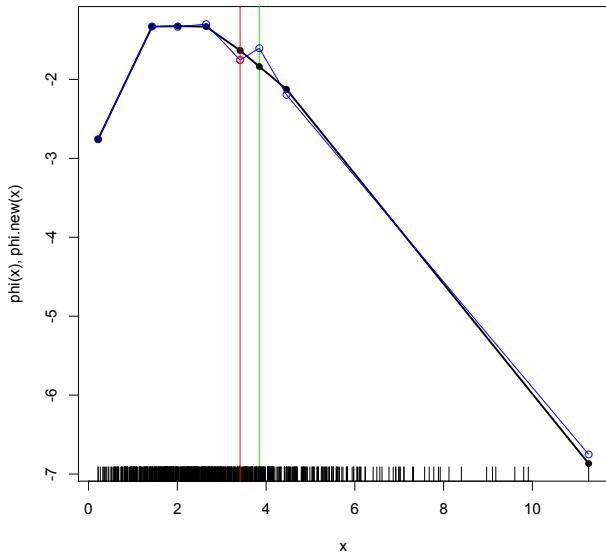
Local optimum: LL = -1.831798367

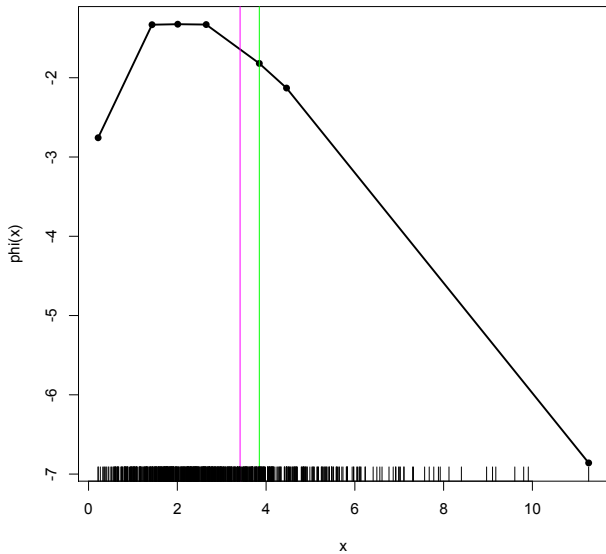


LL = -1.831798367 , dir. deriv. = 0.0025654828

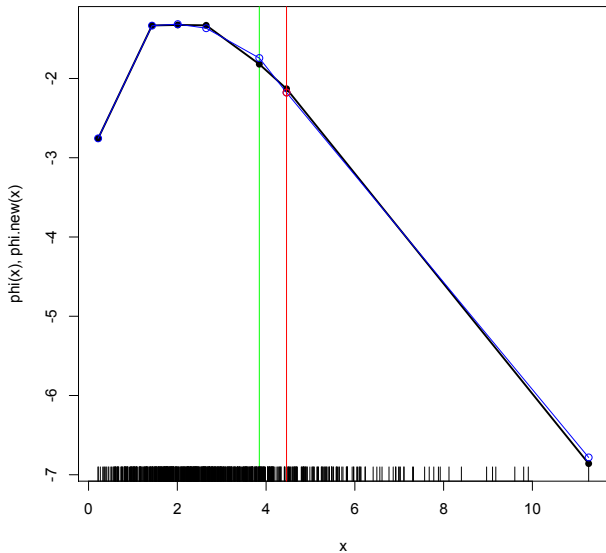


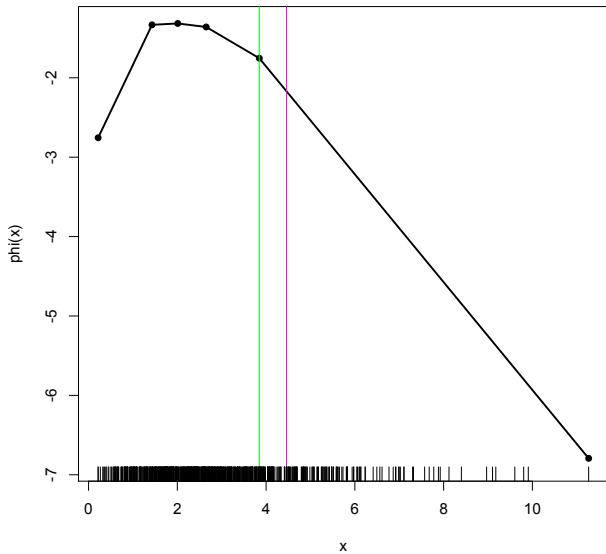
LL = -1.831798367 , dir. deriv. = 0.0033585062





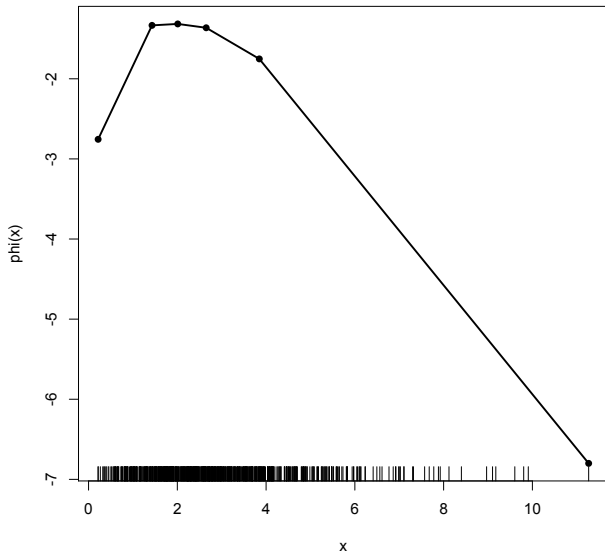
LL = -1.831558774 , dir. deriv. = 0.0007068522



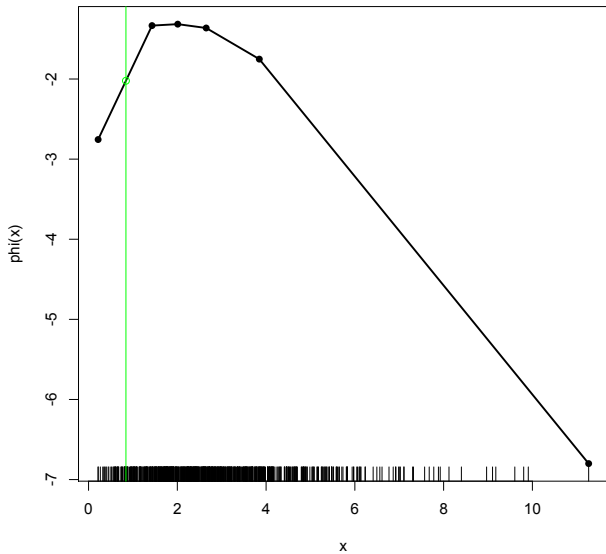


Newton proposals in dimensions 8, 7, 6, 6

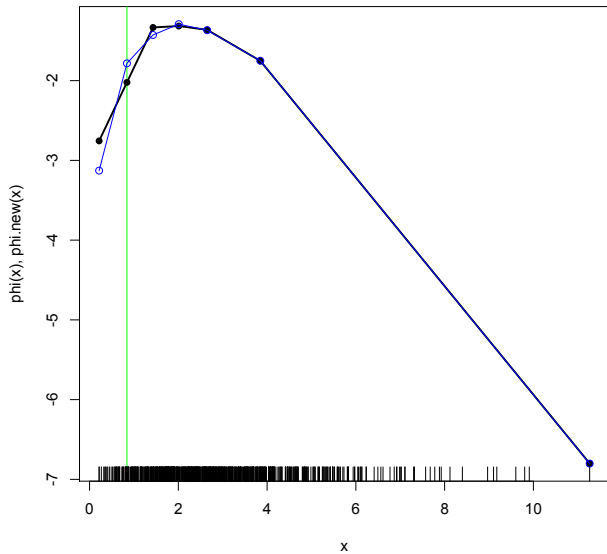
Local optimum: LL = -1.83121385



LL = -1.83121385 , dir. deriv. = 0.002308197

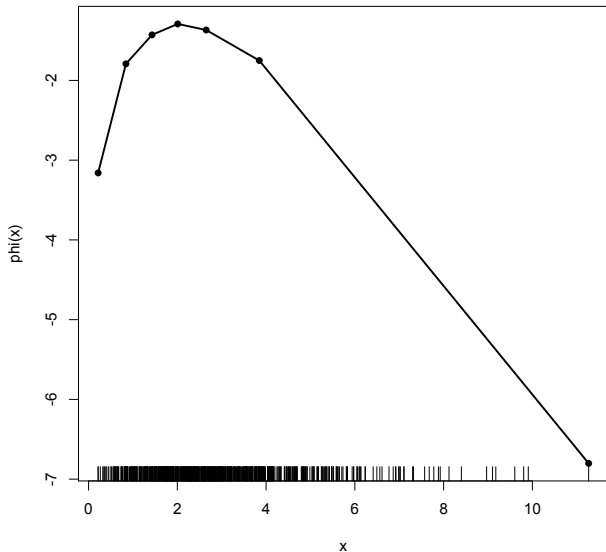


LL = -1.83121385 , dir. deriv. = 0.003558266

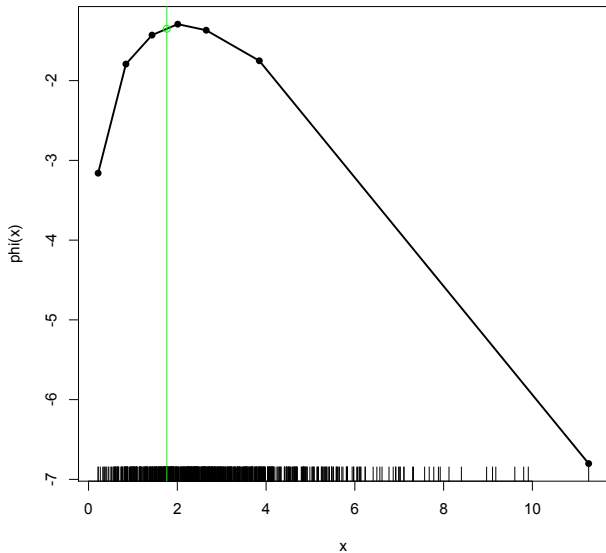


Newton proposals in dimensions 7,7,7,7

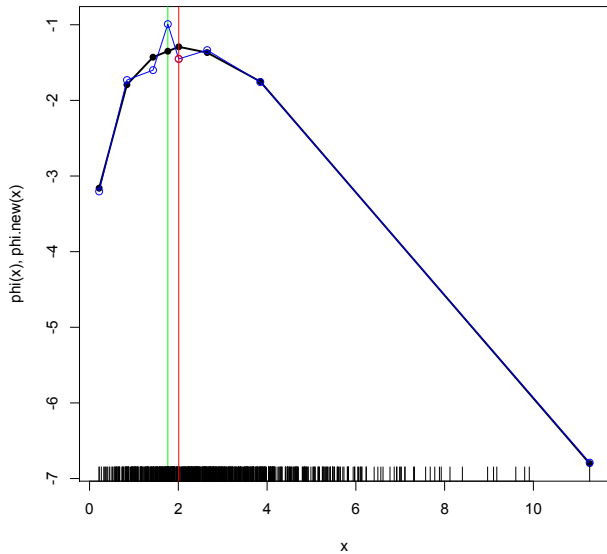
Local optimum: LL = -1.829418286

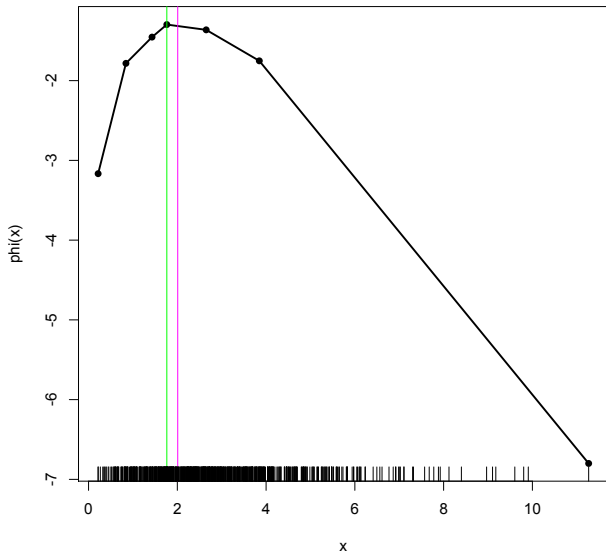


LL = -1.829418286 , dir. deriv. = 0.001941204

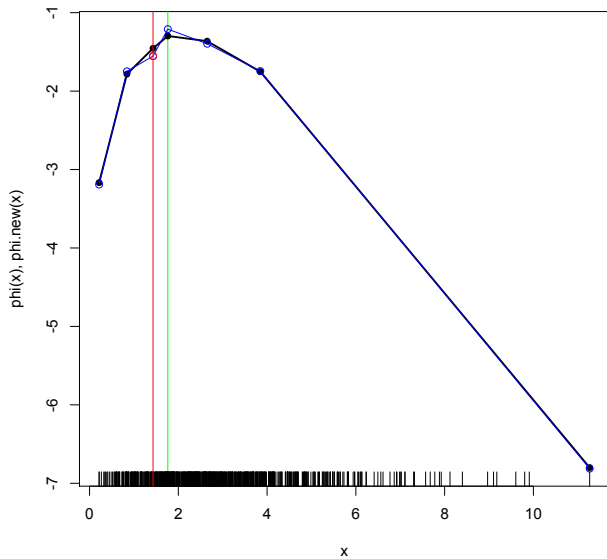


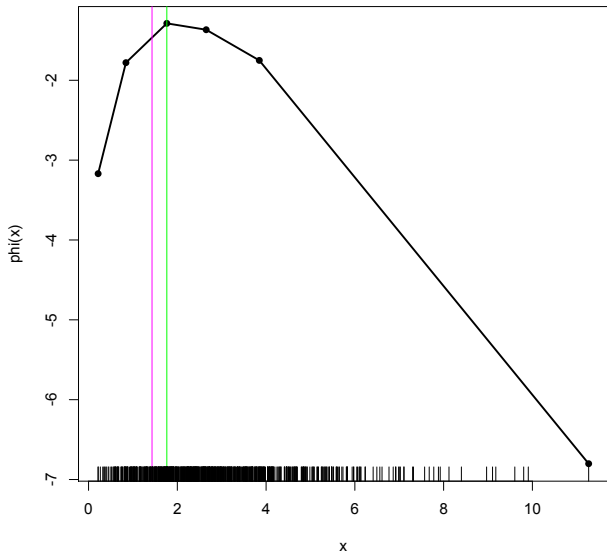
LL = -1.829418286 , dir. deriv. = 0.0071650095



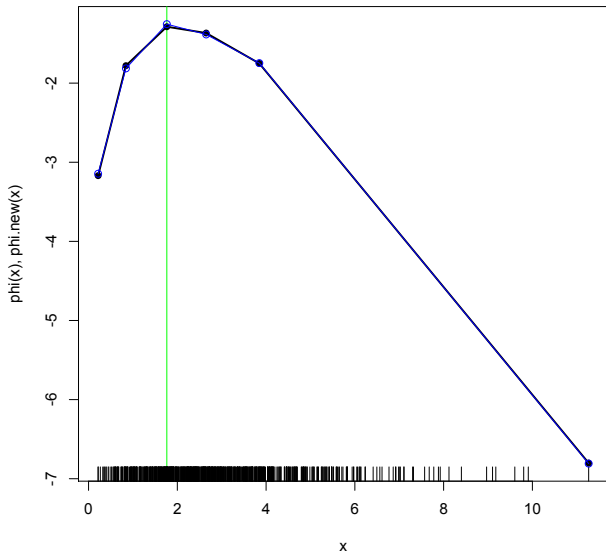


LL = -1.828437401 , dir. deriv. = 0.0011447684



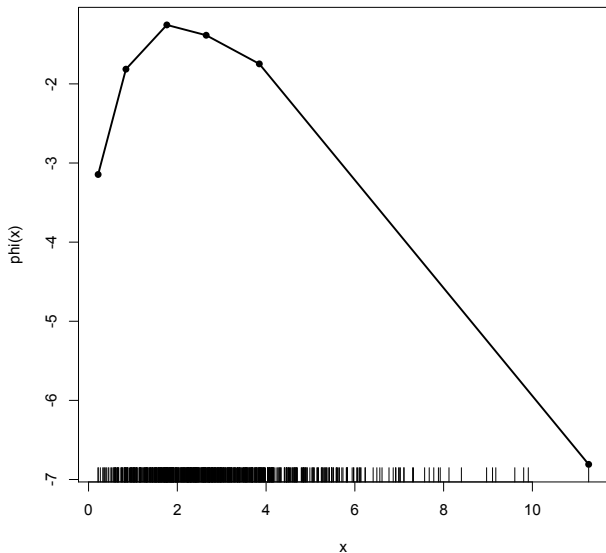


LL = -1.828316099 , dir. deriv. = 0.0001895999

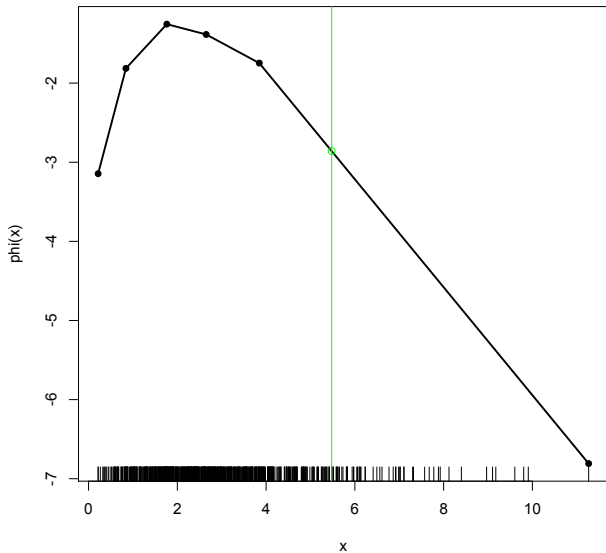


Newton proposals in dimensions 8, 7, 6, 6, 6

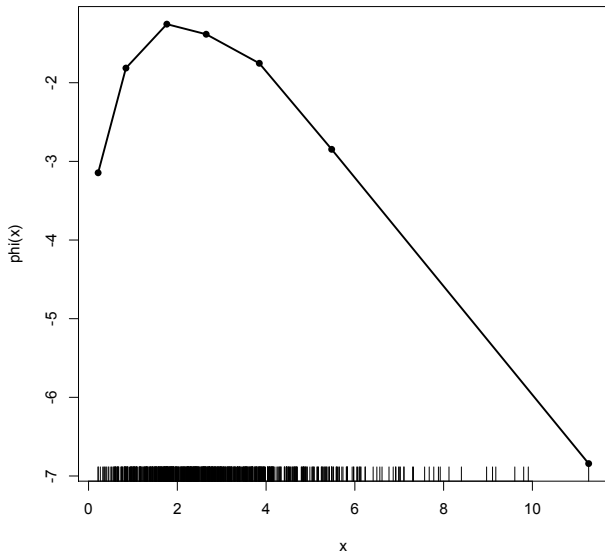
Local optimum: LL = -1.828221389



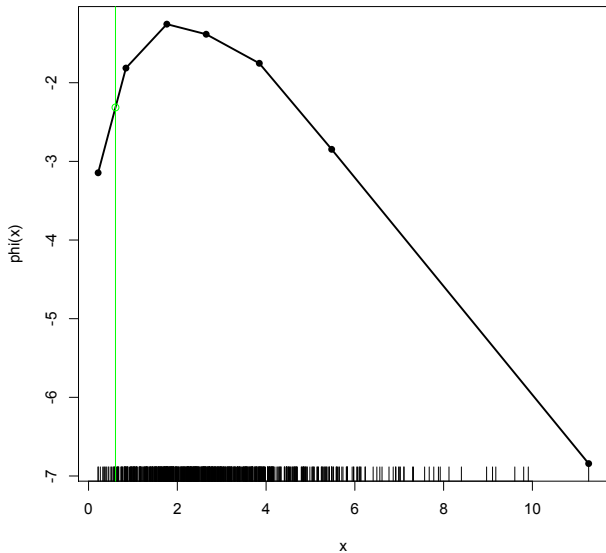
LL = -1.828221389 , dir. deriv. = 0.0007860211



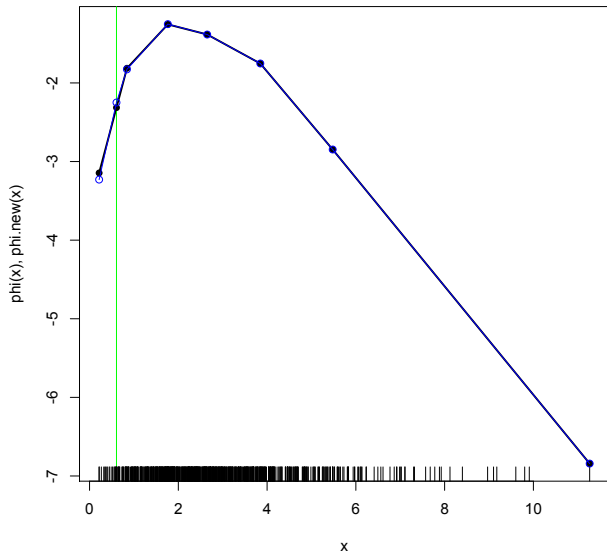
Local optimum: LL = -1.828213874



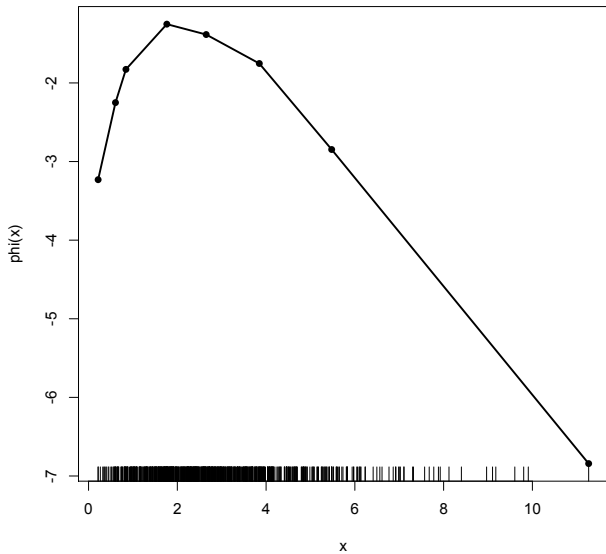
LL = -1.828213874 , dir. deriv. = 0.0001214971



LL = -1.828213874 , dir. deriv. = 8.68781e-05



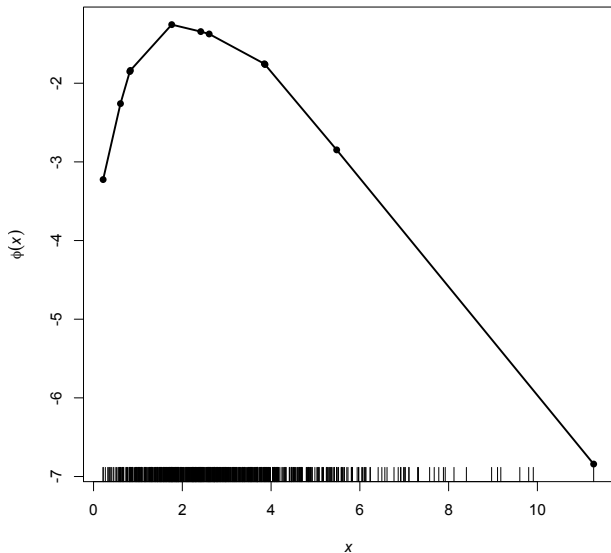
Local optimum: LL = -1.828170565



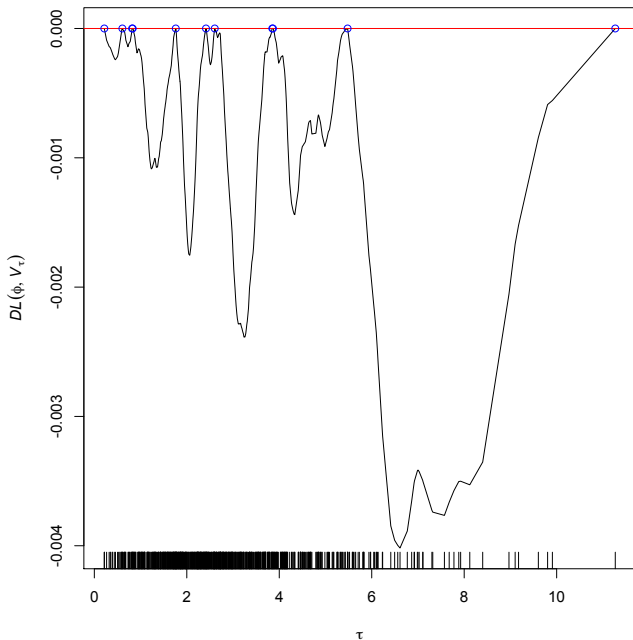
After 14 (modified) local searches, 45 Newton proposals:

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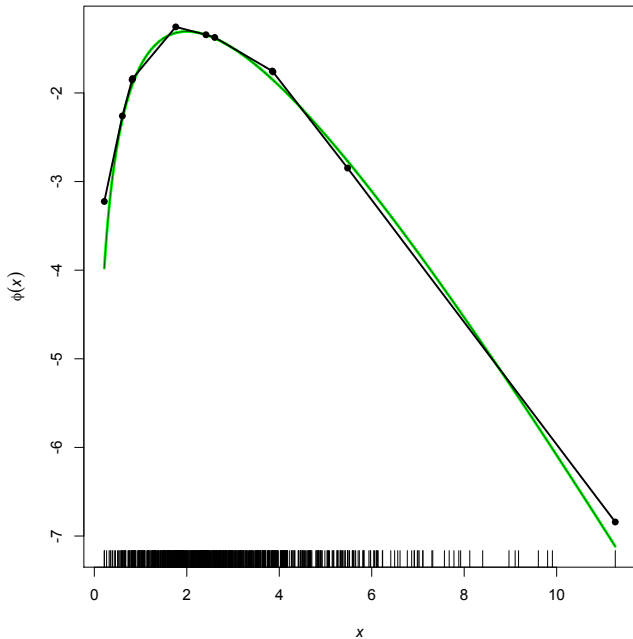
Global optimum: LL = -1.828149162



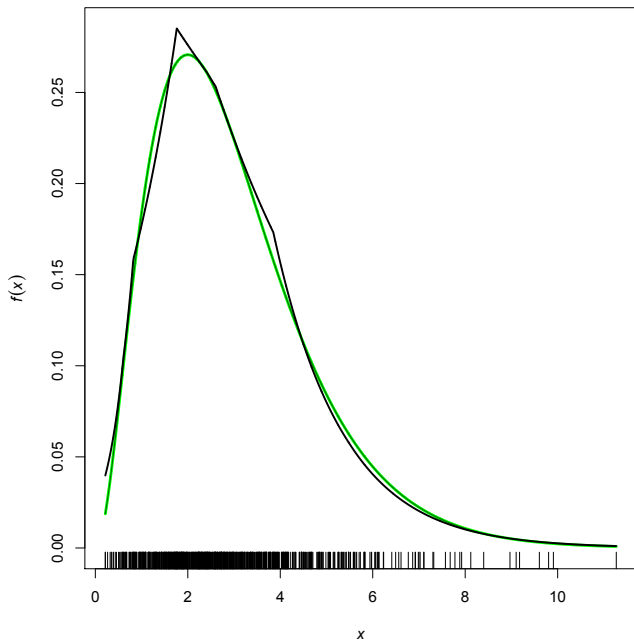
Directional derivatives for extra knot at τ :



Log-densities:

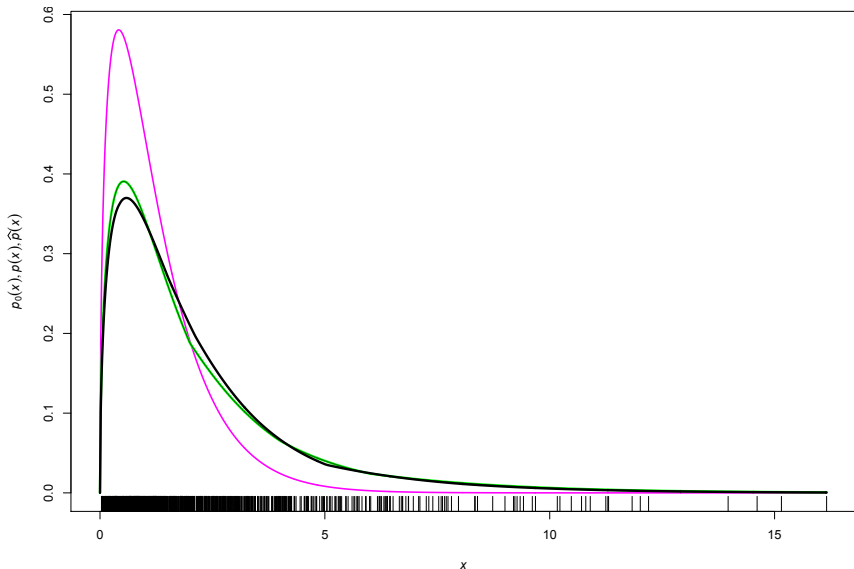


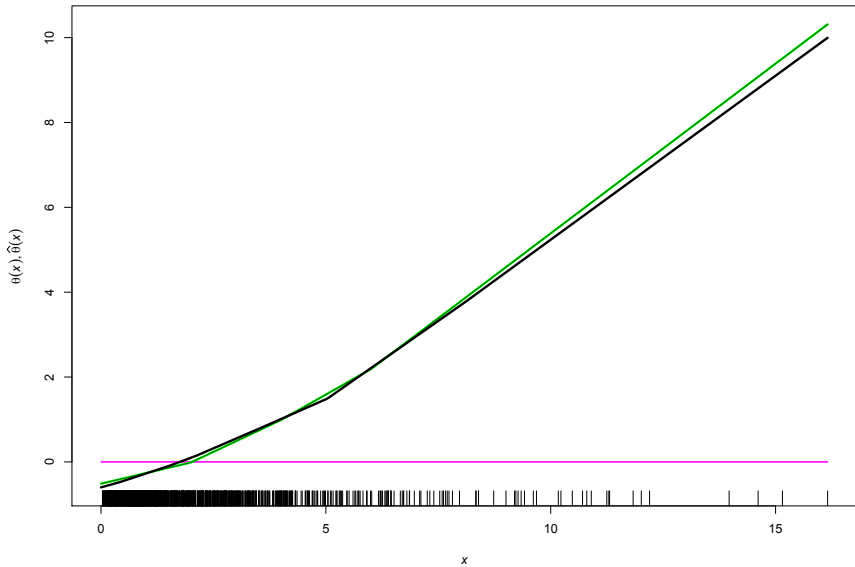
Densities:



Example for Setting 2B.

$n = 1000$ observations from P
 $P_0 = \text{Gamma}(1.5, 1.2)$





Open questions for Settings 2A-B

Suppose we replace discrete \hat{P} with arbitrary distribution.

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Under which conditions on \hat{P} and P_0 exists a unique

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$$\hat{\theta} \in \arg \max_{\theta \in \Theta} \left(\int \theta d\hat{P} - \int e^\theta dP_0 \right) ?$$

What continuity properties has the mapping

$$\hat{P} \mapsto \hat{\theta} ?$$

Open questions for Settings 2A-B

Suppose we replace discrete \hat{P} with arbitrary distribution.

Under which conditions on \hat{P} and P_0 exists a unique

$$\hat{\theta} \in \arg \max_{\theta \in \Theta} \left(\int \theta d\hat{P} - \int e^\theta dP_0 \right) ?$$

What continuity properties has the mapping

$$\hat{P} \mapsto \hat{\theta} ?$$

(Analogous questions for Setting 1 well understood)

References

- ▶ Groeneboom, Jongbloed, Wellner (2008).
The support reduction algorithm for computing nonparametric function estimates in mixture models. *Scand. J. Statist.* 35
- ▶ D., Hüsler, Rufibach (2007/2011).
Active set and EM algorithms for log-concave densities based on complete and censored data.
Technical report, IMSV, University of Bern (arxiv:0707.4643)
- ▶ D., Mösching, Strähl (2018).
Active set algorithms for density estimators under shape-constraints.
In preparation
- ▶ McCullagh, Polson (2012).
Tail inflation. *Biometrika* 99
- ▶ D., Samworth, Schuhmacher (2011).
Approximation by log-concave distributions, with applications to regression. *Ann. Statist.* 39