

Use of piecewise linearization for (un)constrained optimization and ODE integration

Andreas Griewank

with thanks to

HUB: Torsten Bosse, Tom Streubel, Nikolai Strogies,

Uni Paderborn: Andrea Walther, Sabrina Fiege

MIT: Paul Barton, Kamil Khan

Recent Advances in Optimization, July 2013

Smooth stuff I won't talk about (very much)

- Cubic Overestimation with Hessian Updating
- Gauss-Transposed-Broyden for Least Squares

Generalized Derivatives and Semismoothness

- Background and Motivation
- Generalized differentiation rules
- Semismooth Newton Result

Piecewise linearization Approach

- Piecewise linearization rules
- Approximation and Continuity
- Computing Generalized Jacobians

Applications to fundamental tasks

- Nonsmooth equation solving
- (Un)constrained Optimization
- Integration of Lipschitzian Dynamics

Observations on Generalized Hessians

Alternative stabilizations of quadratic model

$$f(x+s) - f(x) \approx m(s) \equiv g^\top s + \frac{1}{2} s^\top B s \text{ with } g \equiv \nabla f(x), B \approx \nabla^2 f(x)$$

Line-search with $B \succ 0$

$$s = \operatorname{argmin}\{m(s)\}$$

$$\alpha \approx \operatorname{argmin}\{f(x + \alpha s)\} \quad \text{and} \quad x_+ = x + \alpha s$$

Trust Region with radius $\Delta > 0$

$$s = \operatorname{argmin}\{m(s) : \|s\| \leq \Delta\}$$

$$\text{if } f(x+s) \ll f(x) \text{ then } x_+ = x + s \text{ else } \Delta_+ \ll \Delta$$

Cubic overestimation with Lipschitz constant $2q > 0$

$$s = \operatorname{argmin}\{m(s) + q\|s\|^3/3\}$$

$$\text{if } f(x+s) \ll f(x) \text{ then } x_+ = x + s \text{ else } q_+ \gg q$$

Alternative stabilizations of quadratic model

$$f(x+s) - f(x) \approx m(s) \equiv g^\top s + \frac{1}{2} s^\top B s \text{ with } g \equiv \nabla f(x), B \approx \nabla^2 f(x)$$

Line-search with $B \succ 0$

$$s = \mathbf{argmin}\{m(s)\}$$

$$\alpha \approx \mathbf{argmin}\{f(x + \alpha s)\} \quad \text{and} \quad x_+ = x + \alpha s$$

Trust Region with radius $\Delta > 0$

$$s = \mathbf{argmin}\{m(s) : \|s\| \leq \Delta\}$$

$$\text{if } f(x+s) \ll f(x) \text{ then } x_+ = x + s \text{ else } \Delta_+ \ll \Delta$$

Cubic overestimation with Lipschitz constant $2q > 0$

$$s = \mathbf{argmin}\{m(s) + q\|s\|^3/3\}$$

$$\text{if } f(x+s) \ll f(x) \text{ then } x_+ = x + s \text{ else } q_+ \gg q$$

Alternative stabilizations of quadratic model

$$f(x+s) - f(x) \approx m(s) \equiv g^\top s + \frac{1}{2} s^\top B s \text{ with } g \equiv \nabla f(x), B \approx \nabla^2 f(x)$$

Line-search with $B \succ 0$

$$s = \mathbf{argmin}\{m(s)\}$$

$$\alpha \approx \mathbf{argmin}\{f(x + \alpha s)\} \quad \text{and} \quad x_+ = x + \alpha s$$

Trust Region with radius $\Delta > 0$

$$s = \mathbf{argmin}\{m(s) : \|s\| \leq \Delta\}$$

$$\text{if } f(x+s) \ll f(x) \text{ then } x_+ = x + s \text{ else } \Delta_+ \ll \Delta$$

Cubic overestimation with Lipschitz constant $2q > 0$

$$s = \mathbf{argmin}\{m(s) + q\|s\|^3/3\}$$

$$\text{if } f(x+s) \ll f(x) \text{ then } x_+ = x + s \text{ else } q_+ \gg q$$

Alternative stabilizations of quadratic model

$$f(x+s) - f(x) \approx m(s) \equiv g^\top s + \frac{1}{2} s^\top B s \text{ with } g \equiv \nabla f(x), B \approx \nabla^2 f(x)$$

Line-search with $B \succ 0$

$$s = \mathbf{argmin}\{m(s)\}$$

$$\alpha \approx \mathbf{argmin}\{f(x + \alpha s)\} \quad \text{and} \quad x_+ = x + \alpha s$$

Trust Region with radius $\Delta > 0$

$$s = \mathbf{argmin}\{m(s) : \|s\| \leq \Delta\}$$

$$\text{if } f(x+s) \ll f(x) \text{ then } x_+ = x + s \text{ else } \Delta_+ \ll \Delta$$

Cubic overestimation with Lipschitz constant $2q > 0$

$$s = \mathbf{argmin}\{m(s) + q\|s\|^3/3\}$$

$$\text{if } f(x+s) \ll f(x) \text{ then } x_+ = x + s \text{ else } q_+ \gg q$$

Step Computation and Properties

As shown by G. and others **global minimum** of the cubic model

$$g(x)^\top s + \frac{1}{2}s^\top Bs + \frac{1}{3}q\|s\|^3$$

is attained at all solutions of the appended linear system

$$(B + \lambda I)s = -g \quad \text{with} \quad \lambda = q\|s\|$$

for which $B(\lambda) \equiv B + \lambda I$ is positive semi-definite.

By eliminating $s(\lambda)$ we obtain a secular equation

$$\varphi(\lambda) \equiv \|s(\lambda)\|^2 \equiv g^\top (B + \lambda I)^{-2} g = \lambda^2 / q^2.$$

where LHS/RHS are convex and monotonic falling/growing.

Need to solve systems:

$$(B + \lambda I)s = -g \quad \text{for various } \lambda \in \mathbb{R}$$

with B subject to shifted BFGS, SR1 or compromise update.
Hessenberg form etc **does not work**, i.e. generates cost of $\mathcal{O}(n^3)$.

First way out: Updating the EVD

$$B = V\Lambda V^\top \quad \text{with diagonal } \Lambda \text{ and orthogonal } V$$

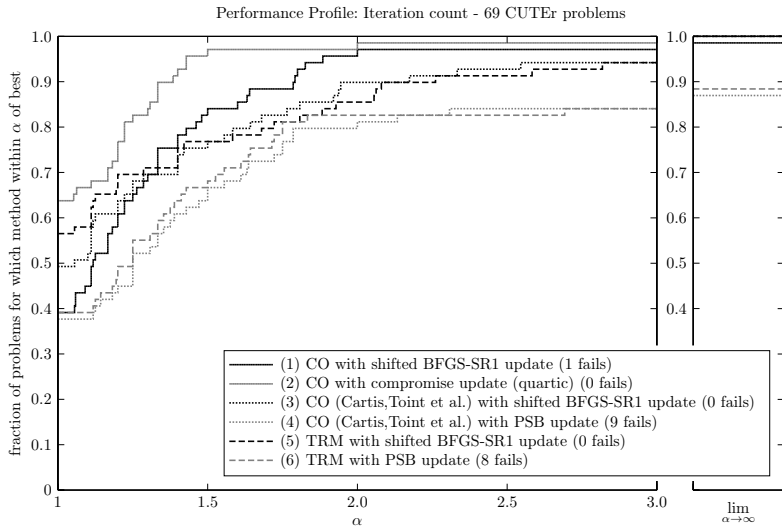
$$B_\pm = B \pm cc^\top = V_\pm \Lambda_\pm V_\pm^\top$$

requires $\mathcal{O}(n^2)$ operations for Λ_\pm via the secular equation and
 $\mathcal{O}((n \log n)^2)$ operations for V_\pm using fast polynomial arithmetic.
But method is **barely** numerically stable even when B is symmetric.

True way out: Nocedal Recurrence ?

Keep B in limited memory product format and apply modified NR!

- Smooth stuff I won't talk about (very much)
- Cubic Overestimation with Hessian Updating



Basic Approach (see also Eldon Haber)

Data assimilation and other least squares require solutions of

$$\min_x \varphi(x) \equiv \frac{1}{2} \|F(x)\|^2 \quad \text{for} \quad F: \mathbb{R}^n \mapsto \mathbb{R}^m$$

quasi-Gauss Newton approach for computing step s at point x

$$B^\top B s = -F'(x)^\top F(x) = -\nabla \varphi(x) \in \mathbb{R}^n$$

using $F'(x) \approx B \in \mathbb{R}^{m \times n}$ and only derivative vectors

$$z \equiv F'(x)^\top t \in \mathbb{R}^n \quad \text{and} \quad y \equiv F'(x) s \in \mathbb{R}^m$$

Two-sided rank one formula

$$B_+(z) = B + r \left[r^\top (F'(x_+) - B) \right] / \|r\|^2 \quad \text{with} \quad r = y - B s$$

Satisfies primal secant condition:

$$B_+ s = r + B s = F'(x_+) s = F(x + s) - F(x) + O(\|s\|^2)$$

Satisfies dual secant condition:

$$B_+^\top z = F'(x_+)^\top z \quad \text{for} \quad r = z \in \mathbb{R}^m$$

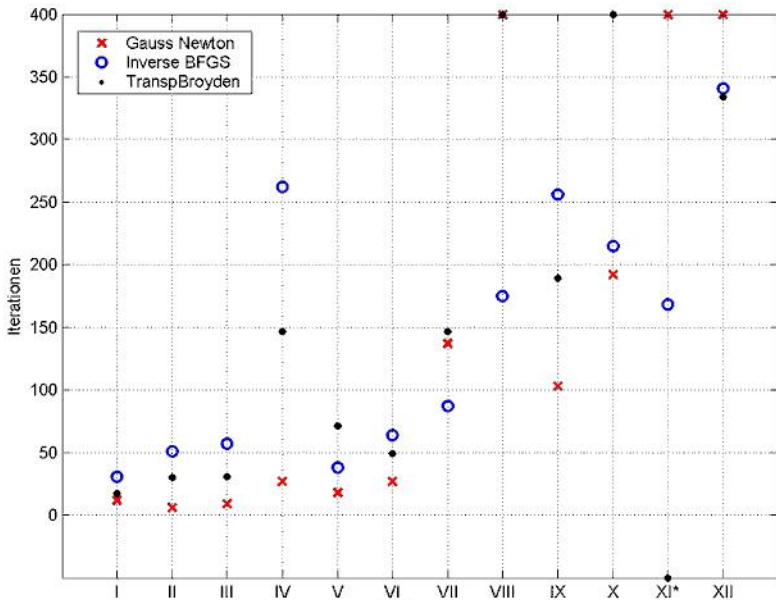
General Properties:

Fixed scale least change \implies bounded deterioration **and**

Heredity in affine case yielding optimal rate in square case.

Use of piecewise linearization for (un)constrained optimization and ODE integration

- └ Smooth stuff I won't talk about (very much)
- └ Gauss-Transposed-Broyden for Least Squares



- └ Smooth stuff I won't talk about (very much)
 - └ Gauss-Transposed-Broyden for Least Squares

Theoretical convergence result:

Assumption: Smoothness and injectivity on level set

$$F \in C^{1,1} \quad \text{and} \quad \inf_{\|F(x)\| \leq \|F(x_0)\| \leq \|F(z)\|} \left\{ \frac{\|F(x) - F(z)\|}{\|z - x\|} \right\} > 0$$

Wedin line-search \implies Square summability

$$\left| \frac{F_+^\top (F_+ - F)}{\|F_+ - F\|^2} - 1 \right| < \varepsilon \implies \sum \|F_+ - F\| < \infty \implies$$

$$\text{mean} \left\{ \frac{1}{\|s\|} \|(F'_+ - B)s\| + \frac{1}{\|r\|} \|(F'_+ - B)^\top r\| + \frac{1}{\|y\|} \|(F'_+ - B)^\top y\| \right\} = 0$$

Average Dennis and Moré \implies Gauss-Newton Rate

$$\text{mean} \left\{ [B^\top B - F'(x)^\top F'(x)] s \right\} = 0 \implies \|s - s^{GN}\| / \|s\| \rightarrow 0$$

Can we turn this into Algebra!?

Directional derivative á la Dini, Hadamard, Clarke

$$F^{??}(\dot{x}; \Delta x) \equiv \limsup_{\substack{x \rightarrow \dot{x} \\ v \rightarrow \Delta x \\ t \searrow 0}} \left[\frac{F(x + tv) - F(x)}{t} \right]$$

Normal cone a la Mordukhovich in \mathbb{R}^n

$$\mathcal{N}(x; M) \equiv \limsup_{z \rightarrow x} \left\{ u^\top \in \mathbb{R}^m : \lim_{M \ni y \rightarrow z} \frac{u^\top (y - z)}{\|y - z\|} = 0 \right\}$$

Computational complexity?

Perturbations on x and Δx require exploration of F in full domain!!!

Can we turn this into Algebra!?

Directional derivative á la Dini, Hadamard, Clarke

$$F^{??}(\dot{x}; \Delta x) \equiv \limsup_{\substack{x \rightarrow \dot{x} \\ v \rightarrow \Delta x \\ t \searrow 0}} \left[\frac{F(x + tv) - F(x)}{t} \right]$$

Normal cone a la Mordukhovich in \mathbb{R}^n

$$\mathcal{N}(x; M) \equiv \limsup_{z \rightarrow x} \left\{ u^\top \in \mathbb{R}^m : \lim_{M \ni y \rightarrow z} \frac{u^\top (y - z)}{\|y - z\|} = 0 \right\}$$

Computational complexity?

Perturbations on x and Δx require exploration of F in full domain!!!

Can we turn this into Algebra!?

Directional derivative á la Dini, Hadamard, Clarke

$$F^{??}(\dot{x}; \Delta x) \equiv \limsup_{\substack{x \rightarrow \dot{x} \\ v \rightarrow \Delta x \\ t \searrow 0}} \left[\frac{F(x + tv) - F(x)}{t} \right]$$

Normal cone a la Mordukhovich in \mathbb{R}^n

$$\mathcal{N}(x; M) \equiv \limsup_{z \rightarrow x} \left\{ u^\top \in \mathbb{R}^m : \lim_{M \ni y \rightarrow z} \frac{u^\top (y - z)}{\|y - z\|} = 0 \right\}$$

Computational complexity?

Perturbations on x and Δx require exploration of F in full domain!!!

Notational Zoo (Subspecies in Lipschitzian Habitat):

Fréchet Derivative: $\partial F(x) \equiv \partial F / \partial x : \mathcal{D} \mapsto \mathbb{R}^{m \times n} \cup \emptyset$

Limiting Jacobians: $\partial^L F(\dot{x}) \equiv \overline{\lim_{x \rightarrow \dot{x}}} \partial F(x) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$

Clarke Jacobians: $\partial^C F(x) \equiv \text{conv}(\partial^L F(x)) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$

Bouligand: $F'(x; \Delta x) \equiv \lim_{t \searrow 0} [F(x + t\Delta x) - F(x)] / t$
 $: \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$
 $: \mathcal{D} \mapsto \text{PL}_h(\mathbb{R}^n, \mathbb{R}^m)$

Piecewise linearization:

$\Delta F(x; \Delta x) : \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$
 $: \mathcal{D} \mapsto \text{PL}(\mathbb{R}^n, \mathbb{R}^m)$

Moriarty Effect by Rademacher ($\mathcal{C}^{0,1} = W^{1,\infty}$)

Almost everywhere all concepts reduce to Fréchet, except PL!!

Notational Zoo (Subspecies in Lipschitzian Habitat):Fréchet Derivative: $\partial F(x) \equiv \partial F / \partial x : \mathcal{D} \mapsto \mathbb{R}^{m \times n} \cup \emptyset$ Limiting Jacobians: $\partial^L F(\dot{x}) \equiv \overline{\lim_{x \rightarrow \dot{x}}} \partial F(x) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$ Clarke Jacobians: $\partial^C F(x) \equiv \text{conv}(\partial^L F(x)) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$ Bouligand: $F'(x; \Delta x) \equiv \lim_{t \searrow 0} [F(x + t\Delta x) - F(x)] / t$ $: \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$ $: \mathcal{D} \mapsto \mathbf{PL}_h(\mathbb{R}^n, \mathbb{R}^m)$

Piecewise linearization:

 $\Delta F(x; \Delta x) : \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$ $: \mathcal{D} \mapsto \mathbf{PL}(\mathbb{R}^n, \mathbb{R}^m)$ Moriarty Effect by Rademacher ($\mathcal{C}^{0,1} = W^{1,\infty}$)

Almost everywhere all concepts reduce to Fréchet, except PL!!

Notational Zoo (Subspecies in Lipschitzian Habitat):Fréchet Derivative: $\partial F(x) \equiv \partial F / \partial x : \mathcal{D} \mapsto \mathbb{R}^{m \times n} \cup \emptyset$ Limiting Jacobians: $\partial^L F(\dot{x}) \equiv \overline{\lim_{x \rightarrow \dot{x}}} \partial F(x) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$ Clarke Jacobians: $\partial^C F(x) \equiv \text{conv}(\partial^L F(x)) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$ Bouligand: $F'(x; \Delta x) \equiv \lim_{t \searrow 0} [F(x + t\Delta x) - F(x)] / t$ $: \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$ $: \mathcal{D} \mapsto \mathbf{PL}_h(\mathbb{R}^n, \mathbb{R}^m)$

Piecewise linearization:

 $\Delta F(x; \Delta x) : \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$ $: \mathcal{D} \mapsto \mathbf{PL}(\mathbb{R}^n, \mathbb{R}^m)$ Moriarty Effect by Rademacher ($\mathcal{C}^{0,1} = W^{1,\infty}$)

Almost everywhere all concepts reduce to Fréchet, except PL!!

Notational Zoo (Subspecies in Lipschitzian Habitat):Fréchet Derivative: $\partial F(x) \equiv \partial F / \partial x : \mathcal{D} \mapsto \mathbb{R}^{m \times n} \cup \emptyset$ Limiting Jacobians: $\partial^L F(\dot{x}) \equiv \overline{\lim_{x \rightarrow \dot{x}}} \partial F(x) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$ Clarke Jacobians: $\partial^C F(x) \equiv \text{conv}(\partial^L F(x)) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$

Bouligand: $F'(x; \Delta x) \equiv \lim_{t \searrow 0} [F(x + t\Delta x) - F(x)]/t$
 $: \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$
 $: \mathcal{D} \mapsto \mathbf{PL}_h(\mathbb{R}^n, \mathbb{R}^m)$

Piecewise linearization:

$$\begin{aligned} \Delta F(x; \Delta x) &: \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m \\ &: \mathcal{D} \mapsto \mathbf{PL}(\mathbb{R}^n, \mathbb{R}^m) \end{aligned}$$

Moriarty Effect by Rademacher ($\mathcal{C}^{0,1} = W^{1,\infty}$)

Almost everywhere all concepts reduce to Fréchet, except PL!!

Notational Zoo (Subspecies in Lipschitzian Habitat):

Fréchet Derivative: $\partial F(x) \equiv \partial F / \partial x : \mathcal{D} \mapsto \mathbb{R}^{m \times n} \cup \emptyset$

Limiting Jacobians: $\partial^L F(\dot{x}) \equiv \overline{\lim_{x \rightarrow \dot{x}}} \partial F(x) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$

Clarke Jacobians: $\partial^C F(x) \equiv \mathbf{conv}(\partial^L F(x)) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$

Bouligand: $F'(x; \Delta x) \equiv \lim_{t \searrow 0} [F(x + t\Delta x) - F(x)]/t$
 $: \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$
 $: \mathcal{D} \mapsto \mathbf{PL}_h(\mathbb{R}^n, \mathbb{R}^m)$

Piecewise linearization:

$$\Delta F(x; \Delta x) : \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$$

$$: \mathcal{D} \mapsto \mathbf{PL}(\mathbb{R}^n, \mathbb{R}^m)$$

Moriarty Effect by Rademacher ($\mathcal{C}^{0,1} = W^{1,\infty}$)

Almost everywhere all concepts reduce to Fréchet, except PL!!

Notational Zoo (Subspecies in Lipschitzian Habitat):

Fréchet Derivative: $\partial F(x) \equiv \partial F / \partial x : \mathcal{D} \mapsto \mathbb{R}^{m \times n} \cup \emptyset$

Limiting Jacobians: $\partial^L F(\dot{x}) \equiv \overline{\lim}_{x \rightarrow \dot{x}} \partial F(x) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$

Clarke Jacobians: $\partial^C F(x) \equiv \mathbf{conv}(\partial^L F(x)) : \mathcal{D} \rightrightarrows \mathbb{R}^{m \times n}$

Bouligand: $F'(x; \Delta x) \equiv \lim_{t \searrow 0} [F(x + t\Delta x) - F(x)]/t$
 $: \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m$
 $: \mathcal{D} \mapsto \mathbf{PL}_h(\mathbb{R}^n, \mathbb{R}^m)$

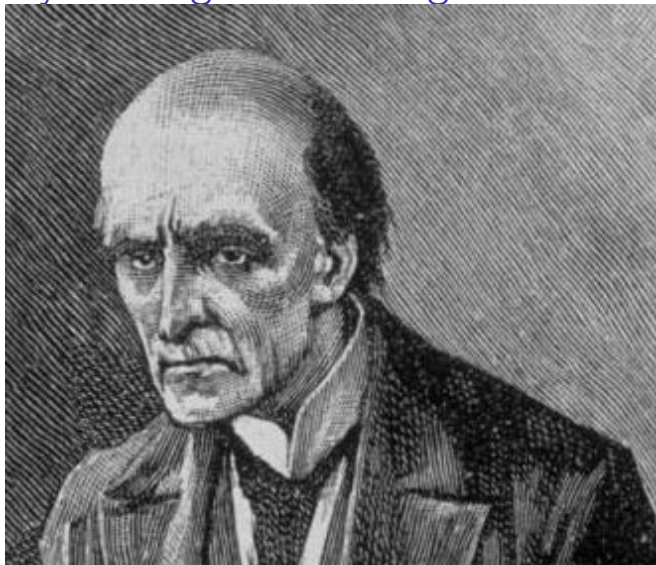
Piecewise linearization:

$$\begin{aligned} \Delta F(x; \Delta x) &: \mathcal{D} \times \mathbb{R}^n \mapsto \mathbb{R}^m \\ &: \mathcal{D} \mapsto \mathbf{PL}(\mathbb{R}^n, \mathbb{R}^m) \end{aligned}$$

Moriarty Effect by Rademacher ($\mathcal{C}^{0,1} = W^{1,\infty}$)

Almost everywhere all concepts reduce to Fréchet, except PL!!

Always lurking in the background: Prof. Moriarty



Relations holding for ∂^L with implications for $\partial^C \equiv \text{conv}(\partial^L)$

- ▶ $\partial^L(\alpha F) = \alpha \partial^L(F)$ for $\alpha \in \mathbb{R}$
- ▶ $\partial^L \begin{pmatrix} G \\ F \end{pmatrix} \subseteq \partial^L F \times \partial^L G \equiv \left\{ \begin{pmatrix} A \\ B \end{pmatrix} : A \in \partial^L(F), B \in \partial^L(G) \right\}$
- ▶ $\partial^L(G \circ F) = \partial^L G(F) \cdot \partial^L F$ if $G \in \mathcal{C}^1(\mathbb{R}^m)$
- ▶ $\partial^L(F \pm G) \subseteq \partial^L F \pm \partial^L G = \{A \pm B : A \in \partial^L F, B \in \partial^L G\}$
- ▶ $\partial^L(f \cdot g) \subseteq g \cdot \partial^L f + f \cdot \partial^L g$
- ▶ $\partial^L |f| \begin{cases} = \partial^L f & \text{when } f > 0 \\ \subseteq -\partial^L \cup \{0\} \cup \partial^L f & \text{when } f = 0 \\ = -\partial^L f & \text{when } f < 0 \end{cases}$

Relations holding for ∂^L with implications for $\partial^C \equiv \text{conv}(\partial^L)$

- ▶ $\partial^L(\alpha F) = \alpha \partial^L(F)$ for $\alpha \in \mathbb{R}$
- ▶ $\partial^L \begin{pmatrix} G \\ F \end{pmatrix} \subseteq \partial^L F \times \partial^L G \equiv \left\{ \begin{pmatrix} A \\ B \end{pmatrix} : A \in \partial^L(F), B \in \partial^L(G) \right\}$
- ▶ $\partial^L(G \circ F) = \partial^L G(F) \cdot \partial^L F$ if $G \in \mathcal{C}^1(\mathbb{R}^m)$
- ▶ $\partial^L(F \pm G) \subseteq \partial^L F \pm \partial^L G = \{A \pm B : A \in \partial^L F, B \in \partial^L G\}$
- ▶ $\partial^L(f \cdot g) \subseteq g \cdot \partial^L f + f \cdot \partial^L g$
- ▶ $\partial^L |f| \begin{cases} = \partial^L f & \text{when } f > 0 \\ \subseteq -\partial^L \cup \{0\} \cup \partial^L f & \text{when } f = 0 \\ = -\partial^L f & \text{when } f < 0 \end{cases}$

Relations holding for ∂^L with implications for $\partial^C \equiv \text{conv}(\partial^L)$

- ▶ $\partial^L(\alpha F) = \alpha \partial^L(F)$ for $\alpha \in \mathbb{R}$
- ▶ $\partial^L \begin{pmatrix} G \\ F \end{pmatrix} \subseteq \partial^L F \times \partial^L G \equiv \left\{ \begin{pmatrix} A \\ B \end{pmatrix} : A \in \partial^L(F), B \in \partial^L(G) \right\}$
- ▶ $\partial^L(G \circ F) = \partial^L G(F) \cdot \partial^L F$ **if** $G \in \mathcal{C}^1(\mathbb{R}^m)$
- ▶ $\partial^L(F \pm G) \subseteq \partial^L F \pm \partial^L G = \{A \pm B : A \in \partial^L F, B \in \partial^L G\}$
- ▶ $\partial^L(f \cdot g) \subseteq g \cdot \partial^L f + f \cdot \partial^L g$
- ▶ $\partial^L |f| \begin{cases} = \partial^L f & \text{when } f > 0 \\ \subseteq -\partial^L \cup \{0\} \cup \partial^L f & \text{when } f = 0 \\ = -\partial^L f & \text{when } f < 0 \end{cases}$

Relations holding for ∂^L with implications for $\partial^C \equiv \text{conv}(\partial^L)$

- ▶ $\partial^L(\alpha F) = \alpha \partial^L(F)$ for $\alpha \in \mathbb{R}$
- ▶ $\partial^L \begin{pmatrix} G \\ F \end{pmatrix} \subseteq \partial^L F \times \partial^L G \equiv \left\{ \begin{pmatrix} A \\ B \end{pmatrix} : A \in \partial^L(F), B \in \partial^L(G) \right\}$
- ▶ $\partial^L(G \circ F) = \partial^L G(F) \cdot \partial^L F$ **if** $G \in \mathcal{C}^1(\mathbb{R}^m)$
- ▶ $\partial^L(F \pm G) \subseteq \partial^L F \pm \partial^L G = \{A \pm B : A \in \partial^L F, B \in \partial^L G\}$
- ▶ $\partial^L(f \cdot g) \subseteq g \cdot \partial^L f + f \cdot \partial^L g$
- ▶ $\partial^L |f| \begin{cases} = \partial^L f & \text{when } f > 0 \\ \subseteq -\partial^L \cup \{0\} \cup \partial^L f & \text{when } f = 0 \\ = -\partial^L f & \text{when } f < 0 \end{cases}$

Relations holding for ∂^L with implications for $\partial^C \equiv \text{conv}(\partial^L)$

- ▶ $\partial^L(\alpha F) = \alpha \partial^L(F)$ for $\alpha \in \mathbb{R}$
- ▶ $\partial^L \begin{pmatrix} G \\ F \end{pmatrix} \subseteq \partial^L F \times \partial^L G \equiv \left\{ \begin{pmatrix} A \\ B \end{pmatrix} : A \in \partial^L(F), B \in \partial^L(G) \right\}$
- ▶ $\partial^L(G \circ F) = \partial^L G(F) \cdot \partial^L F$ if $G \in \mathcal{C}^1(\mathbb{R}^m)$
- ▶ $\partial^L(F \pm G) \subseteq \partial^L F \pm \partial^L G = \{A \pm B : A \in \partial^L F, B \in \partial^L G\}$
- ▶ $\partial^L(f \cdot g) \subseteq g \cdot \partial^L f + f \cdot \partial^L g$
- ▶ $\partial^L |f| \begin{cases} = \partial^L f & \text{when } f > 0 \\ \subseteq -\partial^L \cup \{0\} \cup \partial^L f & \text{when } f = 0 \\ = -\partial^L f & \text{when } f < 0 \end{cases}$

Relations holding for ∂^L with implications for $\partial^C \equiv \text{conv}(\partial^L)$

- ▶ $\partial^L(\alpha F) = \alpha \partial^L(F)$ for $\alpha \in \mathbb{R}$
- ▶ $\partial^L \begin{pmatrix} G \\ F \end{pmatrix} \subseteq \partial^L F \times \partial^L G \equiv \left\{ \begin{pmatrix} A \\ B \end{pmatrix} : A \in \partial^L(F), B \in \partial^L(G) \right\}$
- ▶ $\partial^L(G \circ F) = \partial^L G(F) \cdot \partial^L F$ **if** $G \in \mathcal{C}^1(\mathbb{R}^m)$
- ▶ $\partial^L(F \pm G) \subseteq \partial^L F \pm \partial^L G = \{A \pm B : A \in \partial^L F, B \in \partial^L G\}$
- ▶ $\partial^L(f \cdot g) \subseteq g \cdot \partial^L f + f \cdot \partial^L g$
- ▶ $\partial^L |f| \begin{cases} = \partial^L f & \text{when } f > 0 \\ \subseteq -\partial^L \cup \{0\} \cup \partial^L f & \text{when } f = 0 \\ = -\partial^L f & \text{when } f < 0 \end{cases}$

Direction of inclusions is:

Bad for evaluating (generalized) Jacobians:

since application may result in gross overestimation. Example:

$$\partial^L [|x| - |x|]_{x=0} = \{0\} \neq \{-2, 0, 2\} = \{-1, +1\} + \partial^L [|x|]_{x=0}$$

Good for propagating semi-smoothness:

$$\limsup_{J \in \partial^L F(x+s)} \|F(x+s) - F(x) - Js\| = o(\|s\|)$$

Consequence:

All compositions of smoothies and **abs()** are semismooth !!!

Direction of inclusions is:

Bad for evaluating (generalized) Jacobians:

since application may result in gross overestimation. Example:

$$\partial^L [|x| - |x|]_{x=0} = \{0\} \neq \{-2, 0, 2\} = \{-1, +1\} + \partial^L [|x|]_{x=0}$$

Good for propagating semi-smoothness:

$$\limsup_{J \in \partial^L F(x+s)} \|F(x+s) - F(x) - Js\| = o(\|s\|)$$

Consequence:

All compositions of smoothies and **abs()** are semismooth !!!

Proposition by Kummer, Qi, Sun, Kunisch et al

Semismoothness ensures that generalized Newton:

$$x_{k+1} = x_k - J^{-1}F(x_k) \quad \text{with} \quad J \in \partial^L F(x_k)$$

converges superlinearly to root $x_* \in F^{-1}(0)$ **provided**

$$\|x_0 - x_*\| \leq \rho \quad \text{and} \quad \|J^{-1}\| \leq M < \infty \quad \text{for } J \in \partial^L F(x_*)$$

Doubts concerning Applicability:

- ▶ How small is contraction radius $\rho > 0$?
- ▶ How can we calculate some $J \in \partial^L F(x)$?

Proposition by Kummer, Qi, Sun, Kunisch et al

Semismoothness ensures that generalized Newton:

$$x_{k+1} = x_k - J^{-1}F(x_k) \quad \text{with} \quad J \in \partial^L F(x_k)$$

converges superlinearly to root $x_* \in F^{-1}(0)$ **provided**

$$\|x_0 - x_*\| \leq \rho \quad \text{and} \quad \|J^{-1}\| \leq M < \infty \quad \text{for } J \in \partial^L F(x_*)$$

Doubts concerning Applicability:

- ▶ How small is contraction radius $\rho > 0$?
- ▶ How can we calculate some $J \in \partial^L F(x)$?

Proposition by Kummer, Qi, Sun, Kunisch et al

Semismoothness ensures that generalized Newton:

$$x_{k+1} = x_k - J^{-1}F(x_k) \quad \text{with} \quad J \in \partial^L F(x_k)$$

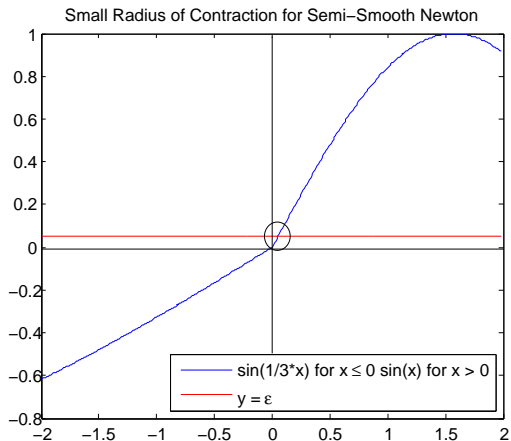
converges superlinearly to root $x_* \in F^{-1}(0)$ **provided**

$$\|x_0 - x_*\| \leq \rho \quad \text{and} \quad \|J^{-1}\| \leq M < \infty \quad \text{for } J \in \partial^L F(x_*)$$

Doubts concerning Applicability:

- ▶ How small is contraction radius $\rho > 0$?
- ▶ How can we calculate some $J \in \partial^L F(x)$?

Contraction radius \leq distance to next kink



Tacit but realistic assumption:

$$y = F(x) : \mathcal{D} \subset \mathbb{R}^n \rightarrow \mathbb{R}^m$$

defined by *long* evaluation loop

$$\begin{array}{ll} \text{input :} & v_{i-n} = x_i \quad \text{for } i = 1 \dots n \\ \text{evaluation :} & v_i = \varphi_i(v_j)_{j \prec i} \quad \text{for } i = 1 \dots \ell \\ \text{output :} & y_{m-i} = v_{\ell-i} \quad \text{for } i = 0 \dots m-1 \end{array}$$

where $v_i \in \mathbb{R}$ for $i = 1-n \dots \ell$ and

$$\varphi_i \in \{+, -, *, /, \exp, \log, \sin, \cos, \dots, \mathbf{abs}, \dots\}$$

Partial pre-ordering

$$j \prec i \iff c_{ij} \equiv \frac{\partial}{\partial v_j} \varphi_i \neq 0.$$

abs covers min, max, $\|\cdot\|_1$, $\|\cdot\|_\infty$, table look-ups

Provided u and w are both finite one has

$$\max(u, w) = \frac{1}{2} [u + w + \mathbf{abs}(u - w)]$$

$$\min(u, w) = \frac{1}{2} [u + w - \mathbf{abs}(u - w)]$$

and data (x_i, y_i) for $i = 0 \dots n$ with slopes s_0 and s_{n+1} on left and right are piecewise linearly interpolated by the formula

$$y = \frac{1}{2} \left[s_0(x - x_0) + y_0 + \sum_{i=0}^n (s_{i+1} - s_i) \mathbf{abs}(x - x_i) + y_n + s_{n+1}(x - x_n) \right]$$

where $s_i = (y_{i+1} - y_i)/(x_{i+1} - x_i)$ represent the inner slopes.

Piecewise Linearization

We wish to determine for *base point* x and *increment* Δx

$$\Delta y \equiv \Delta F(x; \Delta x) = F(x + \Delta x) - F(x) + \mathcal{O}(\|\Delta x\|^2)$$

This can be done by propagating increments according to

Smooth elementals

$$\Delta v_i = \Delta v_j \pm \Delta v_k \quad \text{for} \quad v_i = v_j \pm v_k$$

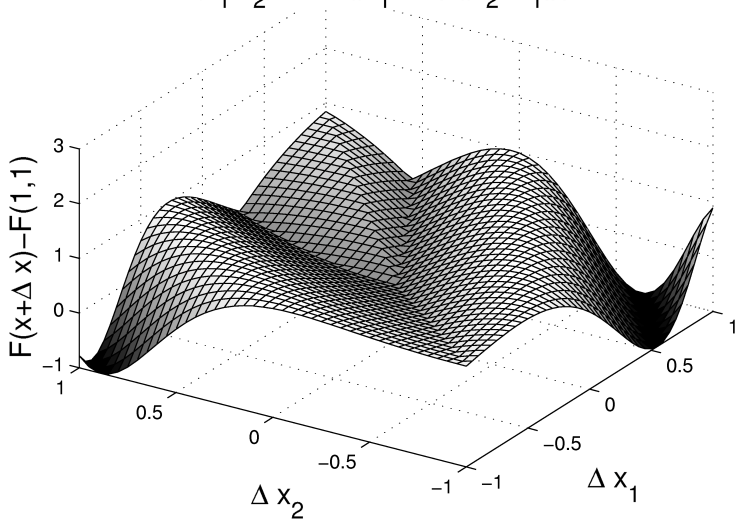
$$\Delta v_i = v_j * \Delta v_k + \Delta v_j * v_k \quad \text{for} \quad v_i = v_j * v_k$$

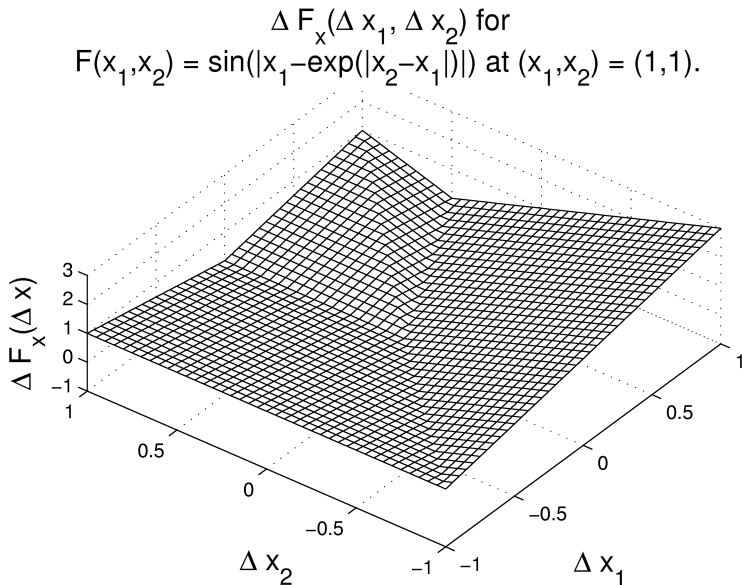
$$\Delta v_i = c_{ij} \Delta v_j \quad \text{with} \quad c_{ij} \equiv \varphi'_i(v_j) \quad \text{for} \quad v_i = \varphi_i(v_j) \neq \mathbf{abs}()$$

Lipschitz Elementals

$$\Delta v_i = \mathbf{abs}(v_j + \Delta v_j) - \mathbf{abs}(v_j) \quad \text{when} \quad v_i = \mathbf{abs}(v_j) .$$

$$F(x_1 + \Delta x_1, x_2 + \Delta x_2) - F(1, 1) \text{ for}$$
$$F(x_1, x_2) = \sin(|x_1| - \exp(|x_2 - x_1|))$$





Linearity and Product Rule

$$F, G : \mathcal{D} \subset \mathbb{R}^n \mapsto \mathbb{R}^m, \alpha, \beta \in \mathbb{R}$$

$$\implies$$

$$\begin{aligned}\Delta[\alpha F + \beta G](x; \Delta x) &= \alpha \Delta F(x, \Delta x) + \beta \Delta G(x, \Delta x) \\ \Delta[F^\top G](x; \Delta x) &= G(x)^\top \Delta F(x, \Delta x) + F(x)^\top \Delta G(x, \Delta x)\end{aligned}$$

Chain Rule

$$F : \mathcal{D} \subset \mathbb{R}^n \mapsto \mathbb{R}^m \quad \text{and} \quad G : E \subset \mathbb{R}^m \mapsto \mathbb{R}^p \quad \text{with} \quad F(\mathcal{D}) \subset E$$

$$\implies$$

$$\Delta[G \circ F](x; \Delta x) = \Delta G(F(x); \Delta F(x, \Delta x))$$

Linearity and Product Rule

$$F, G : \mathcal{D} \subset \mathbb{R}^n \mapsto \mathbb{R}^m, \alpha, \beta \in \mathbb{R}$$

$$\implies$$

$$\begin{aligned}\Delta[\alpha F + \beta G](x; \Delta x) &= \alpha \Delta F(x, \Delta x) + \beta \Delta G(x, \Delta x) \\ \Delta[F^\top G](x; \Delta x) &= G(x)^\top \Delta F(x, \Delta x) + F(x)^\top \Delta G(x, \Delta x)\end{aligned}$$

Chain Rule

$$F : \mathcal{D} \subset \mathbb{R}^n \mapsto \mathbb{R}^m \quad \text{and} \quad G : E \subset \mathbb{R}^m \mapsto \mathbb{R}^p \quad \text{with} \quad F(\mathcal{D}) \subset E$$

$$\implies$$

$$\Delta[G \circ F](x; \Delta x) = \Delta G(F(x); \Delta F(x, \Delta x))$$

Proposition (Approximation and Lipschitz Continuity)

Suppose F is composite Lipschitz on some open neighborhood \mathcal{D} of a closed convex domain $\mathcal{K} \subset \mathbb{R}^n$. Then there exists a constant γ such that for all pairs $\hat{x}, x \in \mathcal{K}$

$$\|F(x) - F(\hat{x}) - \Delta F(\hat{x}; x - \hat{x})\| \leq \gamma \|x - \hat{x}\|^2$$

Moreover, for any pair $\tilde{x}, \hat{x} \in \mathcal{K}$, $\Delta x \in \mathbb{R}^n$, and a constant $\tilde{\gamma}$

$$\|\Delta F(\tilde{x}; \Delta x) - \Delta F(\hat{x}; \Delta x)\| / (1 + \|\Delta x\|) \leq \tilde{\gamma} \|\tilde{x} - \hat{x}\|$$

Finally there is a continuous radius $\rho(\hat{x})$ such that

$$\Delta F(\hat{x}; \Delta x) = F'(\hat{x}; \Delta x) \quad \text{if} \quad \|\Delta x\| < \rho(\hat{x})$$

Locally we reduce to the *homogeneous* piecewise linear $F'(x; \Delta x)$.

Proposition (Approximation and Lipschitz Continuity)

Suppose F is composite Lipschitz on some open neighborhood \mathcal{D} of a closed convex domain $\mathcal{K} \subset \mathbb{R}^n$. Then there exists a constant γ such that for all pairs $\hat{x}, x \in \mathcal{K}$

$$\|F(x) - F(\hat{x}) - \Delta F(\hat{x}; x - \hat{x})\| \leq \gamma \|x - \hat{x}\|^2$$

Moreover, for any pair $\tilde{x}, \hat{x} \in \mathcal{K}$, $\Delta x \in \mathbb{R}^n$, and a constant $\tilde{\gamma}$

$$\|\Delta F(\tilde{x}; \Delta x) - \Delta F(\hat{x}; \Delta x)\| / (1 + \|\Delta x\|) \leq \tilde{\gamma} \|\tilde{x} - \hat{x}\|$$

Finally there is a continuous radius $\rho(\hat{x})$ such that

$$\Delta F(\hat{x}; \Delta x) = F'(\hat{x}; \Delta x) \quad \text{if} \quad \|\Delta x\| < \rho(\hat{x})$$

Locally we reduce to the *homogeneous* piecewise linear $F'(x; \Delta x)$.

Proposition (Approximation and Lipschitz Continuity)

Suppose F is composite Lipschitz on some open neighborhood \mathcal{D} of a closed convex domain $\mathcal{K} \subset \mathbb{R}^n$. Then there exists a constant γ such that for all pairs $\hat{x}, x \in \mathcal{K}$

$$\|F(x) - F(\hat{x}) - \Delta F(\hat{x}; x - \hat{x})\| \leq \gamma \|x - \hat{x}\|^2$$

Moreover, for any pair $\tilde{x}, \hat{x} \in \mathcal{K}$, $\Delta x \in \mathbb{R}^n$, and a constant $\tilde{\gamma}$

$$\|\Delta F(\tilde{x}; \Delta x) - \Delta F(\hat{x}; \Delta x)\| / (1 + \|\Delta x\|) \leq \tilde{\gamma} \|\tilde{x} - \hat{x}\|$$

Finally there is a continuous radius $\rho(\hat{x})$ such that

$$\Delta F(\hat{x}; \Delta x) = F'(\hat{x}; \Delta x) \quad \text{if} \quad \|\Delta x\| < \rho(\hat{x})$$

Locally we reduce to the **homogeneous** piecewise linear $F'(x; \Delta x)$.

Reduced Representation in abs-normal form

After preaccumulation of smoothies

at fixed \hat{x} with strictly lower triangular $L \in \mathbb{R}^{s \times s}$

$$\begin{aligned} \begin{bmatrix} z \\ y \end{bmatrix} &= \begin{bmatrix} \dot{z} + Z(x - \hat{x}) + L(|z| - |\dot{z}|) \\ \dot{y} + J(x - \hat{x}) + Y(|z| - |\dot{z}|) \end{bmatrix} \\ &= \begin{bmatrix} c \\ b \end{bmatrix} + \begin{bmatrix} Z & L \\ J & Y \end{bmatrix} \begin{bmatrix} x \\ |z| \end{bmatrix} = \begin{bmatrix} c \\ b \end{bmatrix} + [C] \begin{bmatrix} x \\ |z| \end{bmatrix} \end{aligned}$$

The signature vector

$\sigma = \mathbf{sign}(z) \in \{-1, 0, 1\}^s$ characterizes **control flow = selection**.

Data c, b and sparse C computable

at cost $\leq (n + s)\mathbf{OPS}(F(x))$ by modification of e.g. ADOL-C

Beating the nonsmoothness superposition problem:

Proposition (Khan & Barton and A. G.)

$$\partial^K F(\dot{x}) \equiv \partial_{\Delta x}^L \Delta F(\dot{x}; \Delta x)|_{\Delta x=0} \subset \partial^L F(x)|_{x=\dot{x}}$$

contains those Jacobians $\partial F_\sigma(\dot{x})$ for which the **tangent cone**

$$T_\sigma \equiv T_{\dot{x}}\{x \in \mathcal{D} : F_\sigma(x) = F(x)\}$$

has a nonempty interior. (i.e. F_σ and ∂F_σ are **conically active**)

Remark

We can find several of them at cost $n \text{ OPS}(F)$ in worst case.

All of them likely a stretch, there could be 2^s different ones.

Beating the nonsmoothness superposition problem:

Proposition (Khan & Barton and A. G.)

$$\partial^K F(\dot{x}) \equiv \partial_{\Delta x}^L \Delta F(\dot{x}; \Delta x)|_{\Delta x=0} \subset \partial^L F(x)|_{x=\dot{x}}$$

contains those Jacobians $\partial F_\sigma(\dot{x})$ for which the **tangent cone**

$$T_\sigma \equiv T_{\dot{x}}\{x \in \mathcal{D} : F_\sigma(x) = F(x)\}$$

has a nonempty interior. (i.e. F_σ and ∂F_σ are **conically active**)

Remark

We can find several of them at cost $n \text{ OPS}(F)$ in worst case.
All of them likely a stretch, there could be 2^s different ones.

Nonsmooth equation solving

Hope:

$$F(\dot{x}) = 0 \quad \text{and} \quad \partial^{??} F(\dot{x}) \text{ 'invertible'}$$

$$\implies$$

$$F(x) = y \approx 0 \quad \text{solvable by} \quad x \leftarrow x + \partial^{??} F(\dot{x})^{-1}(y - F(x))$$

Snag:

(Uniform) Invertibility of $F'(\dot{x}; \cdot)$ and coherent orientation of $\Delta F(\dot{x}; \cdot)$ is **not** stable w.r.t small perturbations in \dot{x} .

Saving grace by Scholtes:

Invertibility of $F'(\dot{x}; \cdot) \implies$ **openness** of F at \dot{x} ,
i.e. nonunique solvability of $F(x) = y \approx 0$, but how to realize?

Nonsmooth equation solving

Hope:

$$F(\dot{x}) = 0 \quad \text{and} \quad \partial^{??} F(\dot{x}) \text{ 'invertible'}$$

$$\implies$$

$$F(x) = y \approx 0 \quad \text{solvable by} \quad x \leftarrow x + \partial^{??} F(\dot{x})^{-1}(y - F(x))$$

Snag:

(Uniform) Invertibility of $F'(\dot{x}; \cdot)$ and coherent orientation of $\Delta F(\dot{x}; \cdot)$ is **not** stable w.r.t small perturbations in \dot{x} .

Saving grace by Scholtes:

Invertibility of $F'(\dot{x}; \cdot) \implies$ **openness** of F at \dot{x} ,
i.e. nonunique solvability of $F(x) = y \approx 0$, but how to realize?

Nonsmooth equation solving

Hope:

$$F(\dot{x}) = 0 \quad \text{and} \quad \partial^{??} F(\dot{x}) \text{ 'invertible'}$$

$$\implies$$

$$F(x) = y \approx 0 \quad \text{solvable by} \quad x \leftarrow x + \partial^{??} F(\dot{x})^{-1}(y - F(x))$$

Snag:

(Uniform) Invertibility of $F'(\dot{x}; \cdot)$ and coherent orientation of $\Delta F(\dot{x}; \cdot)$ is **not** stable w.r.t small perturbations in \dot{x} .

Saving grace by Scholtes:

Invertibility of $F'(\dot{x}; \cdot) \implies$ **openness** of F at \dot{x} ,
i.e. nonunique solvability of $F(x) = y \approx 0$, but how to realize?

Optimization with quadratic overestimation

Under our assumption there exists for given level set

$$\mathcal{N}_0 \equiv \{x \in \mathbb{R}^n : f(x) \leq f(x_0)\}$$

$$\hat{q}(x, s) \equiv |f(x + s) - f(x) - \Delta f(x; s)| / \|s\|^2 \leq \bar{q}(\|s\|)$$

Consequence:

$$\Delta x \equiv \underset{s}{\operatorname{argmin}} (\Delta f(x; s) + q \|s\|^2)$$

$$x \leftarrow x + \Delta x \quad \text{if} \quad f(x + \Delta x) < f(x)$$

$$q_+ = \max(q, \hat{q}(x, \Delta x))$$

has stationary cluster point x_* , i.e.

$$\Delta f(x_*; s) \geq 0 \quad \text{for} \quad s \in \mathbb{R}^n$$

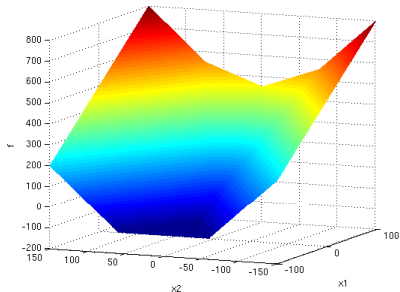
Local = Inner Problem

$$\min_{s \in \mathbb{R}^n} \Delta f(x; s) + \frac{q}{2} \|s\|^2$$

Here we only look at

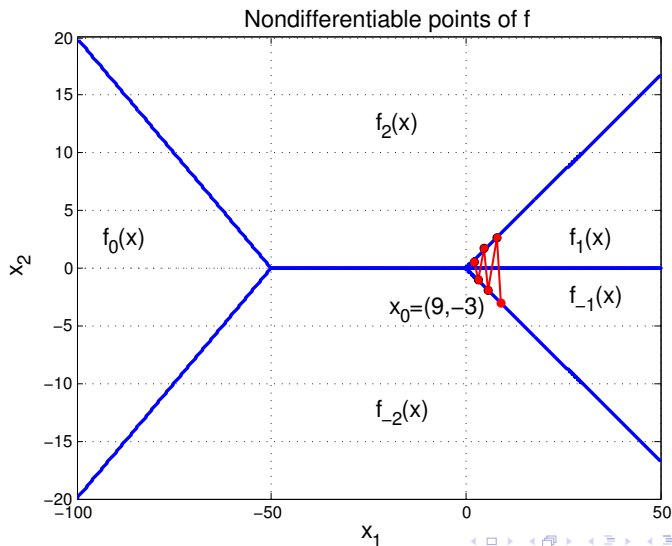
$$\min_{x \in \mathbb{R}^n} f(x)$$

with f continuous and PL.



- ▶ At least, global minimization is NP-hard (\leftarrow SAT3)
- ▶ Classical steepest descent with exact line search may fail even when f is convex as demonstrated by Bonnans et al.

Zig-zagging of Steepest Descent



True steepest descent

Let the search trajectory with starting point $x(0) = x_0$ be defined as

$$-\dot{x} = -d(x) \equiv \mathbf{short}(\partial f(x)) \equiv \mathbf{argmin}\{\|g\| : g \in \partial f(x)\}$$

which are particular solution of differential inclusion $\dot{x} \in -\partial f(x)$.

Solution $x(t)$ satisfies a.e. $g(x(t))^\top \dot{x}(t) \leq -\|d(x(t))\|^2 \implies$

$$0 = \operatorname{essinf}_{t>0} \left| \frac{d}{dt} f(x(t)) \right| \geq \operatorname{essinf}_{t>0} \|d(x(t))\|^2$$

because $f \geq f_*$ on the bounded level set $\mathcal{N}_0 = f^{-1}[f_*, f(x_0)]$.

Thus $x(t)$ has stationary cluster point or limit $x_* \in \mathcal{N}_0$.

Problem: **Zeno** behaviour possible, i.e. a trajectory that includes an infinite number of direction changes in a finite amount of time.

Implementation if PL Case

Abs-normal form yields for any pair $x, d \neq 0$

- ▶ *directionally active gradient* $g = \nabla f(x, d)$
- ▶ *a maximal multiplier* $t_c \in [0, \infty]$ s.t.

$$g \in \partial f(x) \quad \text{and} \quad f(x) + t g^T d = f(x + td) \quad \text{for} \quad 0 \leq t \leq t_c$$

Use bundle subset $G \subset \partial^L f(x)$

define direction as $d = -\text{short}(G) \equiv -\text{argmin}\{\|g\| : g \in G\}$

make sure $\nabla f(x, d) \in G$ before taking serious step

and reduce subsequently $G = \{g \in G : g^T d = -\|d\|^2\}$

Proposition (Griewank, Walther)

Finite convergence to minimizer if $f \in C(\mathbb{R}^n)$ convex and PL.

Implementation if PL Case

Abs-normal form yields for any pair $x, d \neq 0$

- ▶ *directionally active gradient* $g = \nabla f(x, d)$
- ▶ *a maximal multiplier* $t_c \in [0, \infty]$ s.t.

$$g \in \partial f(x) \quad \text{and} \quad f(x) + t g^T d = f(x + td) \quad \text{for} \quad 0 \leq t \leq t_c$$

Use bundle subset $G \subset \partial^L f(x)$

define direction as $d = -\mathbf{short}(G) \equiv -\mathbf{argmin}\{\|g\| : g \in G\}$

make sure $\nabla f(x, d) \in G$ before taking serious step

and reduce subsequently $G = \{g \in G : g^T d = -\|d\|^2\}$

Proposition (Griewank, Walther)

Finite convergence to minimizer if $f \in C(\mathbb{R}^n)$ convex and PL.

Implementation if PL Case

Abs-normal form yields for any pair $x, d \neq 0$

- ▶ *directionally active gradient* $g = \nabla f(x, d)$
- ▶ *a maximal multiplier* $t_c \in [0, \infty]$ s.t.

$$g \in \partial f(x) \quad \text{and} \quad f(x) + t g^T d = f(x + td) \quad \text{for} \quad 0 \leq t \leq t_c$$

Use bundle subset $G \subset \partial^L f(x)$

define direction as $d = -\mathbf{short}(G) \equiv -\mathbf{argmin}\{\|g\| : g \in G\}$

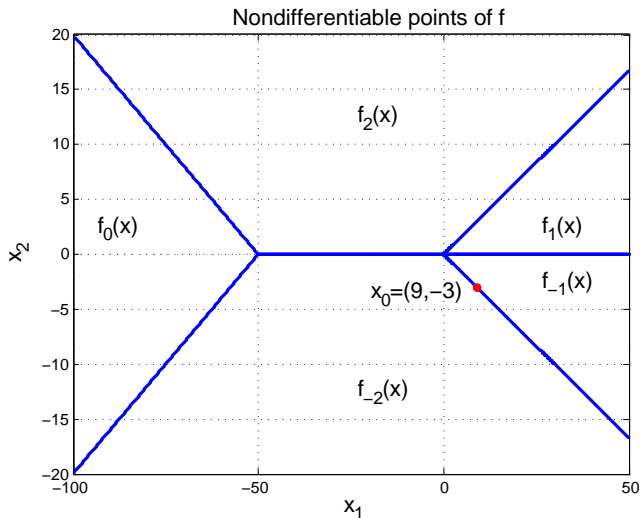
make sure $\nabla f(x, d) \in G$ before taking serious step

and reduce subsequently $G = \{g \in G : g^T d = -\|d\|^2\}$

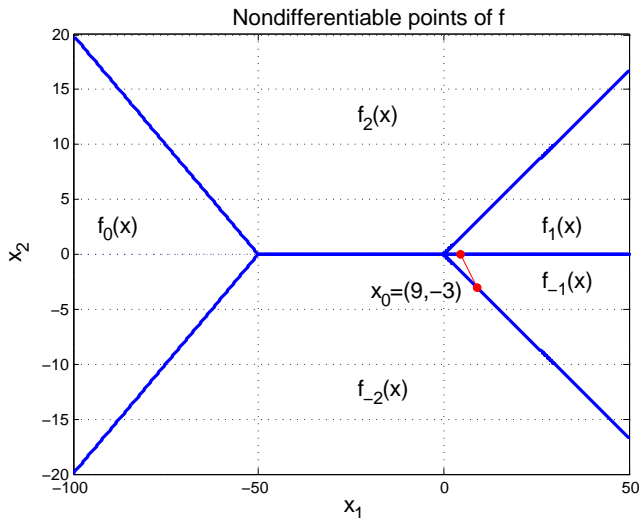
Proposition (Griewank, Walther)

Finite convergence to minimizer if $f \in C(\mathbb{R}^n)$ convex and PL.

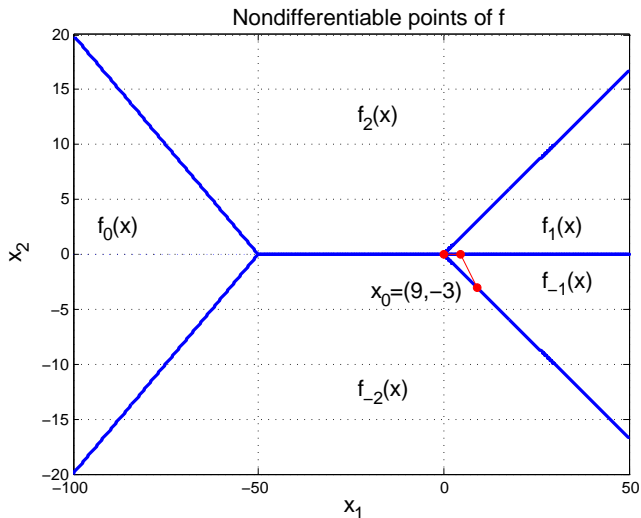
Iteration 1



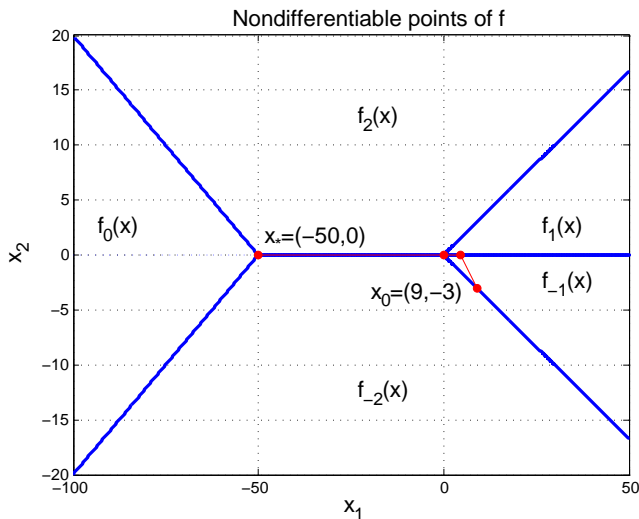
Iteration 2

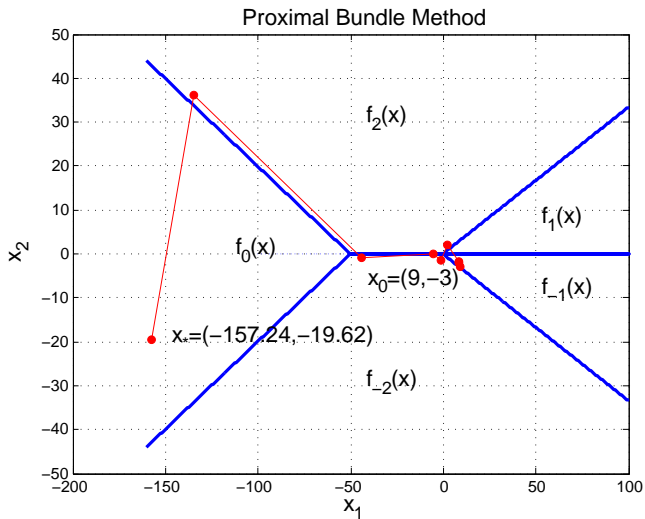


Iteration 3



Iteration 4: Reached optimal point





- └ Applications to fundamental tasks
 - └ Integration of Lipschitzian Dynamics

ODE integration with Lipschitzian RHS

Possibly after space discretization of PDE:

$$\dot{x} \equiv \frac{d}{dt}x(t) = F(x(t)) \quad \text{with} \quad F \in \mathcal{C}^{0,1} = W^{1,\infty}$$

Generalized midpoint rule

With \check{x} current point, \hat{x} next point, $\check{x} = (\check{x} + \hat{x})/2$ and step h

$$\hat{x} - \check{x} = h \int_{-1/2}^{1/2} [F(\check{x}) + \Delta F(\check{x}; (\hat{x} - \check{x})t)] dt$$

maintains global second order with automatic event handling,
realizable by Picard if $1 > h \text{ Lipschitz}(RHS)$, i.e. nonstiffness.

Rolling Stone

$$\ddot{x} = -V'(x) \quad \text{with}$$

$$V(x) = \begin{cases} \frac{1}{2}(1-x)^2 & \text{if } x \geq 1 \\ \frac{1}{2}(1+x)^2 & \text{if } x \leq -1 \\ 0 & \text{else} \end{cases}$$

$$-V'(x) = \begin{cases} 1-x & \text{if } x \geq 1 \\ -x-1 & \text{if } x \leq -1 \\ 0 & \text{else} \end{cases}$$

$$= \min(\max(-x-1, 0), 1-x)$$

$$= -x - \frac{1}{2}|x-1| + \frac{1}{2}|x+1|$$

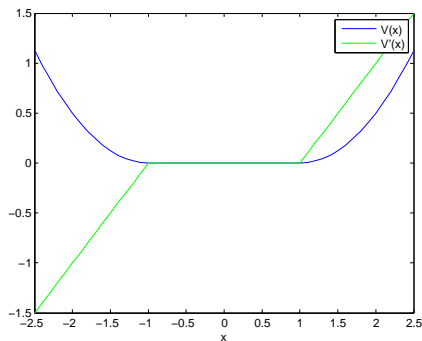


Figure: Rolling Stones Right hand side

Exact solution

$$x(0) = 1, \quad \dot{x}(0) = 1$$

$$x(t) =$$

$$\begin{cases} 1 + \sin(t) & \text{if } t \in [0, \pi) \\ 1 - (t - \pi) & \text{if } t \in [\pi, \pi + 2) \\ -2 - \sin(2 - t) & \text{if } t \in [\pi + 2, 2\pi + 2) \\ t - 3 - 2\pi & \text{if } t \in [2\pi + 2, 2\pi + 4) \end{cases}$$

The total period is $2\pi + 4$.

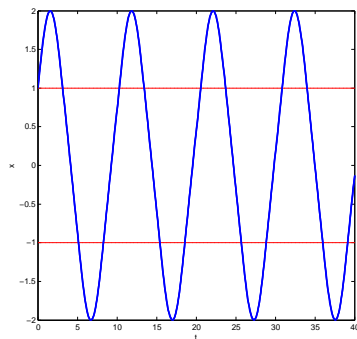
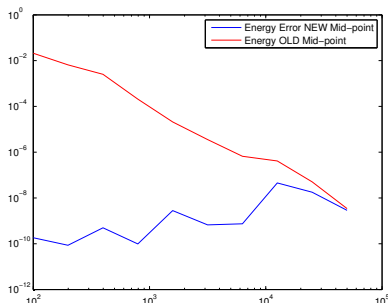
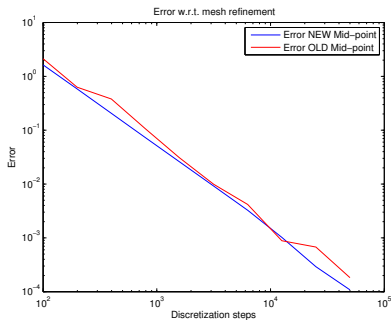


Figure: Exact solution

Use of piecewise linearization for (un)constrained optimization and ODE integration

- └ Applications to fundamental tasks
 - └ Integration of Lipschitzian Dynamics



Problem Definition

$$F(x) = \begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{z} \end{pmatrix} = \begin{pmatrix} \alpha(y - x - f(x)) \\ x - y + z \\ -\beta y \end{pmatrix}$$

$$f(x) = m_1 x + \frac{1}{2}(m_0 - m_1)(|x + 1| - |x - 1|)$$

- x, y are the voltages across C_1 and C_2
- z is the intensity of the electrical current at I
- $f(x)$ is the electrical response of the resistor
- constants are $\alpha = 15.6, \beta = 28, m_0 = -1.143, m_1 = -0.714$

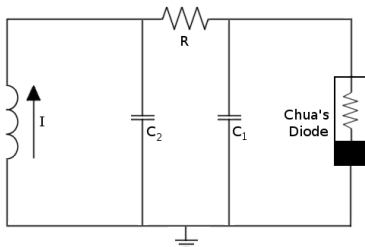
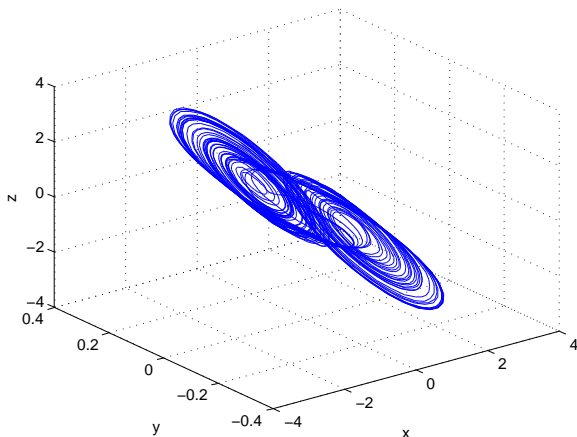


Figure: Chua circuit

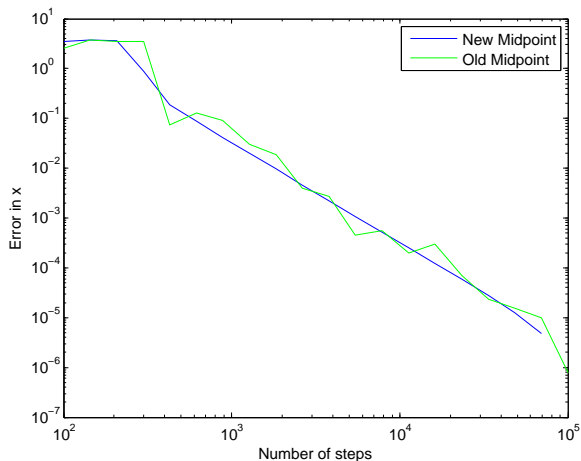
taken from

<http://www.chuacircuits.com/>

Chua circuit



Convergence



When are Hessians symmetric ??

- ▶ Euler, Clairault, Bernoulli, Cauchy, and others tried to prove that matrices of second derivatives are symmetric.
- ▶ Lindelöf demonstrated in 1857 that all their assertions and/or proofs were wrong. Beginner's analysis errors !!

- ▶ A. H. Schwarz, student of Weierstrass proved in 1863

$$g = \nabla f \in \mathcal{C}^1(D) \implies (g')^\top = g' = \nabla^2 f$$

- ▶ Peano provided counter example where in 'some sense'

$$\nabla^2 f(0,0) = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad \text{for} \quad f(x,y) = xy \frac{(x^2 - y^2)}{(x^2 + y^2)}$$

When are Hessians symmetric ??

- ▶ Euler, Clairault, Bernoulli, Cauchy, and others tried to prove that matrices of second derivatives are symmetric.
- ▶ Lindelöf demonstrated in 1857 that all their assertions and/or proofs were wrong. Beginner's analysis errors !!

- ▶ A. H. Schwarz, student of Weierstrass proved in 1863

$$g = \nabla f \in \mathcal{C}^1(D) \implies (g')^\top = g' = \nabla^2 f$$

- ▶ Peano provided counter example where in 'some sense'

$$\nabla^2 f(0,0) = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad \text{for} \quad f(x,y) = xy \frac{(x^2 - y^2)}{(x^2 + y^2)}$$

When are Hessians symmetric ??

- ▶ Euler, Clairault, Bernoulli, Cauchy, and others tried to prove that matrices of second derivatives are symmetric.
- ▶ Lindelöf demonstrated in 1857 that all their assertions and/or proofs were wrong. Beginner's analysis errors !!

- ▶ A. H. Schwarz, student of Weierstrass proved in 1863

$$g = \nabla f \in \mathcal{C}^1(D) \implies (g')^\top = g' = \nabla^2 f$$

- ▶ Peano provided counter example where in 'some sense'

$$\nabla^2 f(0,0) = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad \text{for} \quad f(x,y) = xy \frac{(x^2 - y^2)}{(x^2 + y^2)}$$

When are Hessians symmetric ??

- ▶ Euler, Clairault, Bernoulli, Cauchy, and others tried to prove that matrices of second derivatives are symmetric.
- ▶ Lindelöf demonstrated in 1857 that all their assertions and/or proofs were wrong. Beginner's analysis errors !!
- ▶ A. H. Schwarz, student of Weierstrass proved in 1863

$$g = \nabla f \in \mathcal{C}^1(D) \implies (g')^\top = g' = \nabla^2 f$$

- ▶ Peano provided counter example where in 'some sense'

$$\nabla^2 f(0,0) = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad \text{for} \quad f(x,y) = xy \frac{(x^2 - y^2)}{(x^2 + y^2)}$$

When are Hessians symmetric ??

- ▶ Euler, Clairault, Bernoulli, Cauchy, and others tried to prove that matrices of second derivatives are symmetric.
- ▶ Lindelöf demonstrated in 1857 that all their assertions and/or proofs were wrong. Beginner's analysis errors !!

- ▶ A. H. Schwarz, student of Weierstrass proved in 1863

$$g = \nabla f \in \mathcal{C}^1(D) \implies (g')^\top = g' = \nabla^2 f$$

- ▶ Peano provided counter example where in 'some sense'

$$\nabla^2 f(0,0) = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad \text{for} \quad f(x,y) = xy \frac{(x^2 - y^2)}{(x^2 + y^2)}$$

When are Hessians symmetric ??

- ▶ Euler, Clairault, Bernoulli, Cauchy, and others tried to prove that matrices of second derivatives are symmetric.
- ▶ Lindelöf demonstrated in 1857 that all their assertions and/or proofs were wrong. Beginner's analysis errors !!

- ▶ A. H. Schwarz, student of Weierstrass proved in 1863

$$g = \nabla f \in \mathcal{C}^1(D) \implies (g')^\top = g' = \nabla^2 f$$

- ▶ Peano provided counter example where in 'some sense'

$$\nabla^2 f(0,0) = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} \quad \text{for} \quad f(x,y) = xy \frac{(x^2 - y^2)}{(x^2 + y^2)}$$

Look at the Peano Example

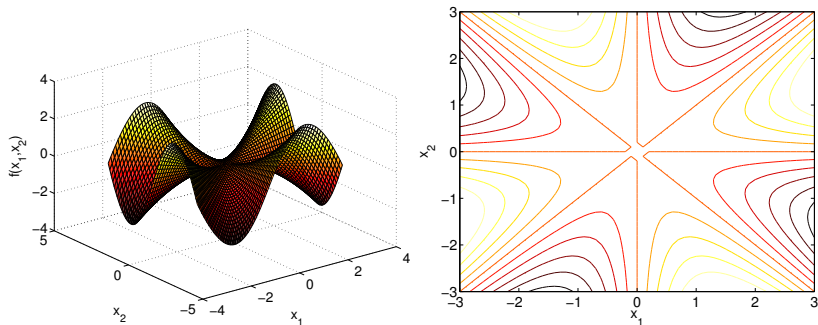


Figure: Peano function and its contour plot

Real Hessians are always symmetric !!

- ▶ Peano Hessian is algebraic fluke, not a Fréchet derivative:

$$g(x + \Delta x) - g(x) \neq g'(x) \Delta x + o(\|\Delta x\|)$$

- ▶ Dieudonné (1960) showed that derivatives of gradients are symmetric where they exist \iff No Perpetuum Mobile !!

- ▶ Limiting and Convexification maintain: $(\partial^C g)^\top = \partial^C g$

- ▶ Griewank et al (2013) are showing the converse, i.e.

$$g \in \mathcal{C}^{0,1}(D) \text{ with } (\partial^C g)^\top = \partial^C g \implies g = \nabla f$$

Real Hessians are always symmetric !!

- ▶ Peano Hessian is algebraic fluke, not a Fréchet derivative:

$$g(x + \Delta x) - g(x) \neq g'(x) \Delta x + o(\|\Delta x\|)$$

- ▶ Dieudonné (1960) showed that derivatives of gradients are symmetric where they exist \iff No Perpetuum Mobile !!
- ▶ Limiting and Convexification maintain: $(\partial^C g)^\top = \partial^C g$
- ▶ Griewank et al (2013) are showing the converse, i.e.

$$g \in \mathcal{C}^{0,1}(D) \text{ with } (\partial^C g)^\top = \partial^C g \implies g = \nabla f$$

Real Hessians are always symmetric !!

- ▶ Peano Hessian is algebraic fluke, not a Fréchet derivative:

$$g(x + \Delta x) - g(x) \neq g'(x) \Delta x + o(\|\Delta x\|)$$

- ▶ Dieudonné (1960) showed that derivatives of gradients are symmetric where they exist \iff **No Perpetuum Mobile !!**

- ▶ Limiting and Convexification maintain: $(\partial^C g)^\top = \partial^C g$

- ▶ Griewank et al (2013) are showing the converse, i.e.

$$g \in \mathcal{C}^{0,1}(D) \text{ with } (\partial^C g)^\top = \partial^C g \implies g = \nabla f$$

Real Hessians are always symmetric !!

- ▶ Peano Hessian is algebraic fluke, not a Fréchet derivative:

$$g(x + \Delta x) - g(x) \neq g'(x) \Delta x + o(\|\Delta x\|)$$

- ▶ Dieudonné (1960) showed that derivatives of gradients are symmetric where they exist \iff **No Perpetuum Mobile !!**

- ▶ Limiting and Convexification maintain: $(\partial^C g)^\top = \partial^C g$

- ▶ Griewank et al (2013) are showing the converse, i.e.

$$g \in \mathcal{C}^{0,1}(D) \text{ with } (\partial^C g)^\top = \partial^C g \implies g = \nabla f$$

Real Hessians are always symmetric !!

- ▶ Peano Hessian is algebraic fluke, not a Fréchet derivative:

$$g(x + \Delta x) - g(x) \neq g'(x) \Delta x + o(\|\Delta x\|)$$

- ▶ Dieudonné (1960) showed that derivatives of gradients are symmetric where they exist \iff **No Perpetuum Mobile !!**
- ▶ Limiting and Convexification maintain: $(\partial^C g)^\top = \partial^C g$
- ▶ Griewank et al (2013) are showing the converse, i.e.

$$g \in \mathcal{C}^{0,1}(D) \text{ with } (\partial^C g)^\top = \partial^C g \implies g = \nabla f$$

Real Hessians are always symmetric !!

- ▶ Peano Hessian is algebraic fluke, not a Fréchet derivative:

$$g(x + \Delta x) - g(x) \neq g'(x) \Delta x + o(\|\Delta x\|)$$

- ▶ Dieudonné (1960) showed that derivatives of gradients are symmetric where they exist \iff **No Perpetuum Mobile !!**
- ▶ Limiting and Convexification maintain: $(\partial^C g)^\top = \partial^C g$
- ▶ Griewank et al (2013) are showing the converse, i.e.

$$g \in \mathcal{C}^{0,1}(D) \text{ with } (\partial^C g)^\top = \partial^C g \implies g = \nabla f$$

Generalized Hessian of Peano

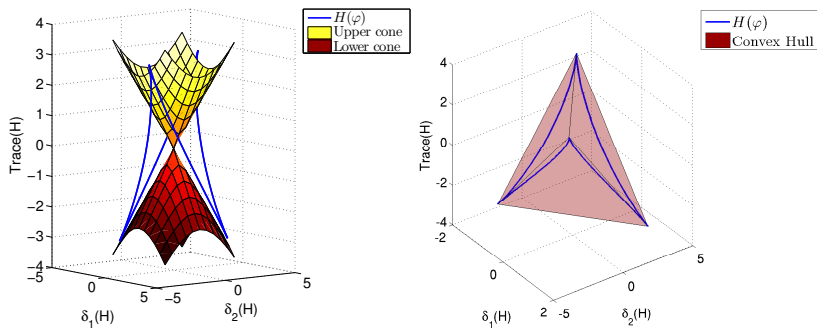


Figure: Hessians circling definite cone with four extremal cusps

Summary and tentative conclusions

- ▶ Practical functions are semi-smooth and their linearization goes further than we thought, but not quite far enough.
- ▶ Yes, we can compute generalized Jacobians! They are not only essential in the sense of Scholtes but conically active.
- ▶ But, semi-smooth Newton only yields convergence from points where combinatorial aspects have been resolved.
- ▶ Piecewise linearization facilitates nonsmooth equation solving, optimization, integration of Lipschitzian ODEs...
- ▶ Lipschitzian gradients have symmetric generalized Hessians that are computable by piecewise linearization
- ▶ Next on the agenda: solving algebraic and differential inclusions as well as bang-bang optimal control problems.

Summary and tentative conclusions

- ▶ Practical functions are semi-smooth and their linearization goes further than we thought, but not quite far enough.
- ▶ Yes, we can compute generalized Jacobians! They are not only essential in the sense of Scholtes but conically active.
- ▶ But, semi-smooth Newton only yields convergence from points where combinatorial aspects have been resolved.
- ▶ Piecewise linearization facilitates nonsmooth equation solving, optimization, integration of Lipschitzian ODEs...
- ▶ Lipschitzian gradients have symmetric generalized Hessians that are computable by piecewise linearization
- ▶ Next on the agenda: solving algebraic and differential inclusions as well as bang-bang optimal control problems.

Summary and tentative conclusions

- ▶ Practical functions are semi-smooth and their linearization goes further than we thought, but not quite far enough.
- ▶ Yes, we can compute generalized Jacobians! They are not only essential in the sense of Scholtes but conically active.
- ▶ But, semi-smooth Newton only yields convergence from points where combinatorial aspects have been resolved.
- ▶ Piecewise linearization facilitates nonsmooth equation solving, optimization, integration of Lipschitzian ODEs...
- ▶ Lipschitzian gradients have symmetric generalized Hessians that are computable by piecewise linearization
- ▶ Next on the agenda: solving algebraic and differential inclusions as well as bang-bang optimal control problems.

Summary and tentative conclusions

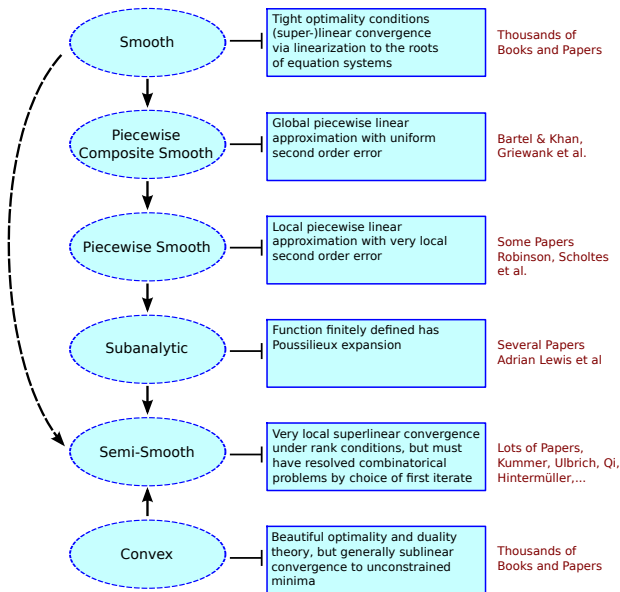
- ▶ Practical functions are semi-smooth and their linearization goes further than we thought, but not quite far enough.
- ▶ Yes, we can compute generalized Jacobians! They are not only essential in the sense of Scholtes but conically active.
- ▶ But, semi-smooth Newton only yields convergence from points where combinatorial aspects have been resolved.
- ▶ Piecewise linearization facilitates nonsmooth equation solving, optimization, integration of Lipschitzian ODEs...
- ▶ Lipschitzian gradients have symmetric generalized Hessians that are computable by piecewise linearization
- ▶ Next on the agenda: solving algebraic and differential inclusions as well as bang-bang optimal control problems.

Summary and tentative conclusions

- ▶ Practical functions are semi-smooth and their linearization goes further than we thought, but not quite far enough.
- ▶ Yes, we can compute generalized Jacobians! They are not only essential in the sense of Scholtes but conically active.
- ▶ But, semi-smooth Newton only yields convergence from points where combinatorial aspects have been resolved.
- ▶ Piecewise linearization facilitates nonsmooth equation solving, optimization, integration of Lipschitzian ODEs...
- ▶ Lipschitzian gradients have symmetric generalized Hessians that are computable by piecewise linearization
- ▶ Next on the agenda: solving algebraic and differential inclusions as well as bang-bang optimal control problems.

Summary and tentative conclusions

- ▶ Practical functions are semi-smooth and their linearization goes further than we thought, but not quite far enough.
- ▶ Yes, we can compute generalized Jacobians! They are not only essential in the sense of Scholtes but conically active.
- ▶ But, semi-smooth Newton only yields convergence from points where combinatorial aspects have been resolved.
- ▶ Piecewise linearization facilitates nonsmooth equation solving, optimization, integration of Lipschitzian ODEs...
- ▶ Lipschitzian gradients have symmetric generalized Hessians that are computable by piecewise linearization
- ▶ Next on the agenda: solving algebraic and differential inclusions as well as bang-bang optimal control problems.



Final greetings from Prof. Moriarty

