Nonconvex, Nonsmooth Optimization by Gradient Sampling

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involving joint work with

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Outline

Outline

Motivations

Gradient Sampling (GS)

Adaptive GS

SQP-GS

Future Work

Nonlinear/convex optimization research

Emphasis today on solving structured optimization problems.

- In most cases, structure means convex.
- Often goes further, e.g., seeking sparsity, low matrix rank, low total variation.
- Nemirovski, Nesterov, Wright, ...
- d'Aspremont, Lan, Recht, Yin, ...
- Focus on large-scale problems needing only an approximate solution.
- First-order methods, optimal algorithms, regularization, ...

My work

I am interested in algorithms for unstructured nonlinear optimization.

- For one thing, unstructured means nonconvex.
- Other work: Inexact Newton methods for large-scale optimization.
- Other work: Model/data inconsistencies leading to infeasibility and degeneracy.
- This talk: Enhancing practical NLO methods for handling nonsmoothness.

Widespread use of optimization requires accommodating algorithms.

- Accommodating algorithms can be the "go-to" methods for new problems.
- Accommodating algorithms are all we have for very hard problems.

Deterministic optimization methods based on randomized models

Unconstrained minimization of an objective function $f : \mathbb{R}^n \to \mathbb{R}$:

- No gradient info available? e.g., objective values from simulations
- Only some gradient info available? e.g., large-scale machine learning
- Subdifferential not available? e.g., any unstructured nonsmooth problem

Randomized algorithms offer computational flexibility and other benefits.

- DFO: randomization leads to better poised models.
- SO: (batch) stochastic gradient methods have nice practical/theoretical behavior.
- UO: gradient sampling...

Contributions

Gradient sampling is a general-purpose method for nonconvex, nonsmooth problems.

- We dramatically reduce per-iteration and overall computational cost.
- Nothing is lost in terms of global convergence guarantees.
- We extend the methodology and theory to constrained optimization.

Outline

Unconstrained nonconvex, nonsmooth optimization

Consider the unconstrained problem

$$\boxed{\min_x \; f(x)}$$

where f is locally Lipschitz and continuously differentiable in (dense) $\mathcal{D} \subset \mathbb{R}^n$.

Unconstrained nonconvex, nonsmooth optimization

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where f is locally Lipschitz and continuously differentiable in (dense) $\mathcal{D} \subset \mathbb{R}^n$.

- Let
$$\mathbb{B}_\epsilon(\overline{x}) := \{x \mid \|x - \overline{x}\| \leq \epsilon\}$$
- $\overline{x}$ is stationary if
$$0 \in \partial f(\overline{x}) := \bigcap_{\epsilon > 0} \operatorname{cl}\operatorname{conv} \nabla f(\mathbb{B}_\epsilon(\overline{x}) \cap \mathcal{D})$$
- $\overline{x}$ is ϵ-stationary if
$$0 \in \partial_\epsilon f(\overline{x}) := \operatorname{cl}\operatorname{conv} \partial f(\mathbb{B}_\epsilon(\overline{x}))$$

Gradient sampling (GS) idea

At x_k, let $x_{k0} := x_k$ and sample $\{x_{k1}, \ldots, x_{kp}\} \subset \mathbb{B}_\epsilon(x_k) \cap \mathcal{D}$, yielding:

$$\begin{aligned} X_k &:= \{x_{k0}, \quad x_{k1}, \quad \cdots, \quad x_{kp}\} && \text{(sample points)} \\ G_k &:= \begin{bmatrix} g_{k0} & g_{k1} & \cdots & g_{kp} \end{bmatrix} && \text{(sample gradients)} \end{aligned}$$

The ϵ-subdifferential is approximated by the convex hull of the sampled gradients:

$$\begin{aligned} \partial_\epsilon f(x_k) &= \operatorname{cl}\operatorname{conv} \partial f(\mathbb{B}_\epsilon(x_k)) \\ &\approx \operatorname{conv}\{g_{k0}, g_{k1}, \ldots, g_{kp}\} \end{aligned}$$

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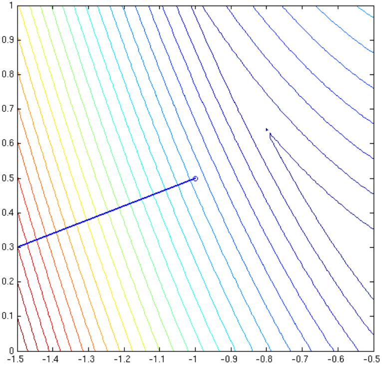
- Compute the projection of 0 onto the convex hull of the sampled gradients:

$$\boxed{g_k := \operatorname{Proj}(0 | \operatorname{conv}\{g_{k0}, g_{k1}, \ldots, g_{kp}\})}$$

Then, $d_k = -g_k$ is an approximate ϵ-steepest descent step.

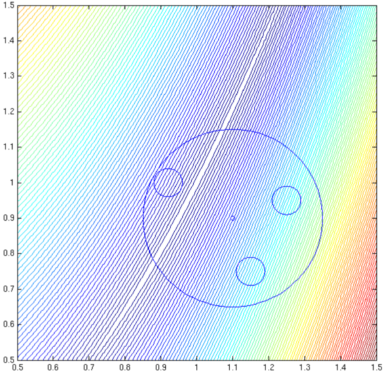
GS illustration

$$\min_x \; 10|x_2 - x_1^2| + (1 - x_1)^2 \;\; \text{at } x_k = (-1, \tfrac{1}{2})$$



GS illustration

$$\min_x \; 10|x_2 - x_1^2| + (1 - x_1)^2 \quad \text{at } x_k = (1.1, 0.9)$$



GS method

for $k = 0, 1, 2, \ldots$

- Sample $p \geq n+1$ points $\{x_{k1}, \ldots, x_{kp}\} \subset \mathbb{B}_\epsilon(x_k) \cap \mathcal{D}$.
- Compute $d_k \leftarrow -g_k$ by computing the projection

$$g_k = \text{Proj}(0 | \operatorname{conv}\{g_{k0}, g_{k1}, \ldots, g_{kp}\}).$$

- Backtrack from $\alpha_k \leftarrow 1$ to satisfy the sufficient decrease condition

$$f(x_k + \alpha_k d_k) \leq f(x_k) - \eta \alpha_k \|d_k\|^2.$$

- Update $x_{k+1} \approx x_k + \alpha_k d_k$ (to ensure $x_{k+1} \in \mathcal{D}$).
- If $\|d_k\| \leq \epsilon$, then reduce ϵ.

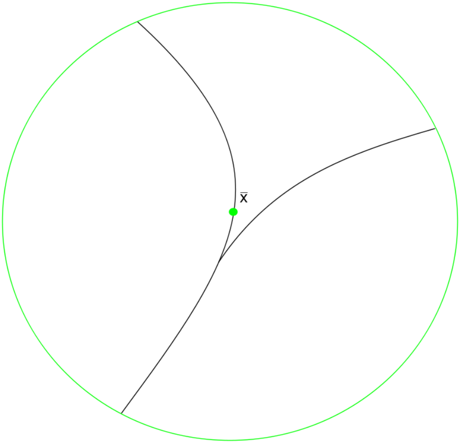
(See Burke, Lewis, and Overton (2005) and Kiwiel (2007).)

Global convergence of GS

Theorem: Let f be locally Lipschitz and continuously differentiable on an open dense $\mathcal{D} \subset \mathbb{R}^n$. Then, w.p.1, $f(x_k) \to -\infty$ or every cluster point of $\{x_k\}$ is stationary for f.

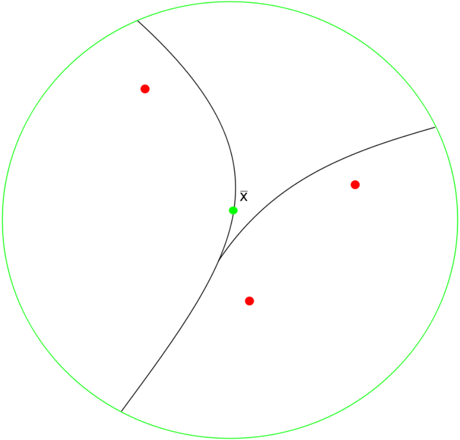
(See Burke, Lewis, and Overton (2005) and Kiwiel (2007).)

Illustration of critical part of proof



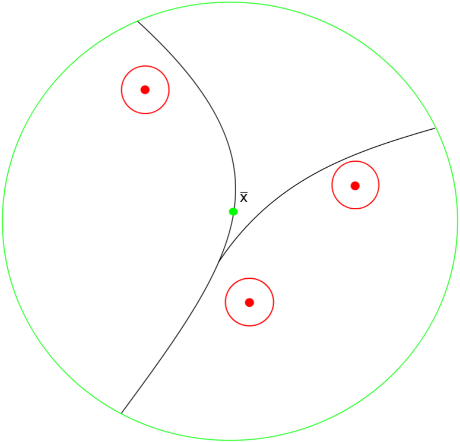
Near $\overline{x}$, the GS algorithm ideally computes $\text{Proj}(0|\partial_\epsilon f(\overline{x}))$.

Illustration of critical part of proof



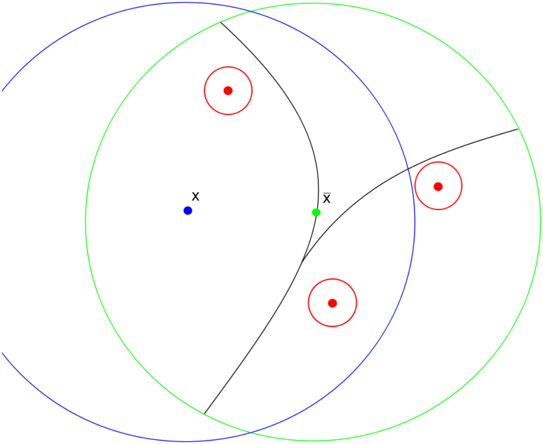
By continuity, there exists $\{y_{ki}\}_{i=1,\ldots,p}$ such that $\text{Proj}(0|\{\nabla f(y_{ki})\}) \approx \text{Proj}(0|\partial_\epsilon f(\overline{x}))$.

Illustration of critical part of proof



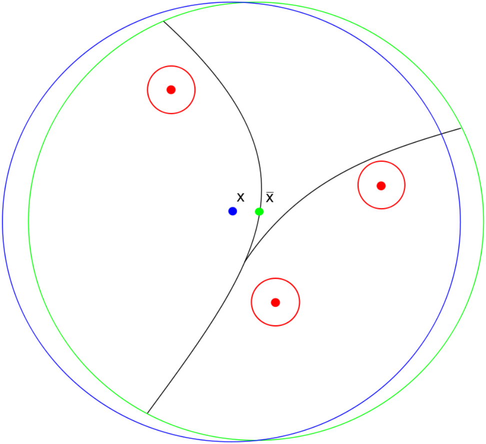
The same holds for sufficiently small neighborhoods about the y_{ki}'s.

Illustration of critical part of proof



Far from $\overline{x}$, the algorithm does not necessarily approximate $\text{Proj}(0|\partial_\epsilon f(\overline{x}))$ well.

Illustration of critical part of proof



However, it can in a sufficiently small neighborhood of $\overline{x}$.

Local models in GS

Computing the projection is equivalent to solving the dual subproblem:

$$\max_{\lambda} \; f(x_k) - \tfrac{1}{2}\|G_k\lambda\|^2$$
$$\text{s.t. } e^T\lambda = 1, \;\; \lambda \geq 0.$$

The corresponding primal subproblem is to compute d_k to minimize

$$q(d; X_k) := f(x_k) + \max_{x \in X_k}\{\nabla f(x)^T d\} + \tfrac{1}{2}\|d\|^2.$$

If all gradients about $\overline{x}$ were available, then we would ideally compute $\overline{d}$ minimizing

$$q(d; \mathbb{B}_\epsilon(\overline{x}) \cap \mathcal{D}) = f(\overline{x}) + \max_{x \in \mathbb{B}_\epsilon(\overline{x}) \cap \mathcal{D}}\{\nabla f(x)^T d\} + \tfrac{1}{2}\|d\|^2.$$

Critical lemma

Let the sample space be

$$\mathcal{S}_\epsilon(x_k) := \{x_k\} \times \prod_1^p (\mathbb{B}_\epsilon(x_k) \cap \mathcal{D})$$

and consider the set

$$\mathcal{T}_{\epsilon,\omega}(x_k, \overline{x}) = \{X_k \in \mathcal{S}_\epsilon(x_k) \mid \Delta q(d_k; X_k) \leq \Delta q(\overline{d}; \mathbb{B}_\epsilon(\overline{x}) \cap \mathcal{D}) + \omega\}.$$

Lemma: For any $\omega > 0$, there exists $\zeta > 0$ and a nonempty set $\mathcal{T}$ such that for all $x_k \in \mathbb{B}(\overline{x}, \zeta)$ we have $\mathcal{T} \subset \mathcal{T}_{\epsilon,\omega}(x_k, \overline{x})$.

(That is, in a sufficiently small neighborhood of $\overline{x}$, there exists a sample set revealing $\Delta q(\overline{d}; \mathbb{B}_\epsilon(\overline{x}) \cap \mathcal{D})$ with arbitrarily good, though not necessarily perfect, accuracy.)

Sketch of proof: Follows from Carathéodory's theorem.

Global convergence of GS

Theorem: Let f be locally Lipschitz and continuously differentiable on an open dense $\mathcal{D} \subset \mathbb{R}^n$. Then, w.p.1, $f(x_k) \to -\infty$ or every cluster point of $\{x_k\}$ is stationary for f.

Sketch of proof: If $f(x_k) \nrightarrow -\infty$, then

$$\alpha_k \Delta q(d_k; X_k) \to 0.$$

If $\epsilon \nrightarrow 0$, then for all large k,

$$\Delta q(d_k; X_k) = \tfrac{1}{2}\|d_k\|^2 > \tfrac{1}{2}\epsilon^2, \qquad (\star)$$

and it can be shown that $x_k \to \bar{x}$ and $\alpha_k \to 0$. However, w.p.1, this will not occur:

- If $\bar{x}$ is ϵ-stationary, then w.p.1 we will obtain a sample set in $\mathcal{T}$ yielding $\Delta q(d_k; X_k) \leq \frac{1}{2}\epsilon^2$, contradicting $(\star)$.
- If $\bar{x}$ is not ϵ-stationary, then w.p.1 we will obtain a subsequence with α_k bounded away from zero, contradicting $\alpha_k \to 0$.

Thus, w.p.1, $\epsilon \to 0$ and any cluster point $\bar{x}$ is stationary for f.

Outline

Practical issues

Practical limitations of GS:

- $p \geq n + 1$ gradient evaluations per iteration
- All subproblems solved from scratch
- Behaves like steepest descent(?)

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Practical limitations of GS:

- $p \geq n + 1$ gradient evaluations per iteration
- All subproblems solved from scratch
- Behaves like steepest descent(?)

Proposed enhancements:

- Adaptive sampling; only $O(1)$ gradients per iteration (Kiwiel (2010))
- Warm-started subproblem solves
- "Hessian" approximations for quadratic term

Adaptive Gradient Sampling (AGS)

At x_k, we had:

$$
\begin{aligned}
X_k &:= \left\{x_{k0}, \quad x_{k1}, \quad \cdots, \quad x_{kp}\right\} && \text{(sample points)} \\
G_k &:= \left[g_{k0} \quad g_{k1} \quad \cdots \quad g_{kp}\right] && \text{(sample gradients)}
\end{aligned}
$$

At x_{k+1}, we

- maintain sample points still within radius ϵ; (this allows warm-starting!)
- throw out gradients outside of radius;
- sample 1 (or some) new gradients.

How can we maintain global convergence?

- If sample size is at least $n+1$, then proceed as usual; else, truncate line search.

Primal-dual pair of subproblems

Recall the primal-dual pair of GS subproblems:

$$\boxed{\begin{aligned} &\max_{z,d}\ z + \tfrac{1}{2}d^T d \\ &\ \text{s.t. } f(x_k)e + G_k^T d \le ze \end{aligned}} \qquad \boxed{\begin{aligned} &\max_{\lambda}\ f(x_k) - \tfrac{1}{2}\lambda^T G_k^T G_k \lambda \\ &\ \text{s.t. } e^T\lambda = 1,\ \lambda \ge 0 \end{aligned}}$$

Primal-dual pair of subproblems (variable-metric)

Recall the primal-dual pair of GS subproblems:

$$\begin{aligned}\max_{z,d}\ & z + \tfrac{1}{2}d^T d \\ \text{s.t. } & f(x_k)e + G_k^T d \le ze\end{aligned}$$

$$\begin{aligned}\max_{\lambda}\ & f(x_k) - \tfrac{1}{2}\lambda^T G_k^T G_k \lambda \\ \text{s.t. } & e^T\lambda = 1,\ \lambda \ge 0\end{aligned}$$

Introduce second order terms with "Hessian" approximations:

$$\begin{aligned}\max_{z,d}\ & z + \tfrac{1}{2}d^T H_k d \\ \text{s.t. } & f(x_k)e + G_k^T d \le ze\end{aligned}$$

$$\begin{aligned}\max_{\lambda}\ & f(x_k) - \tfrac{1}{2}\lambda^T G_k^T W_k G_k \lambda \\ \text{s.t. } & e^T\lambda = 1,\ \lambda \ge 0\end{aligned}$$

How should H_k (or W_k) be chosen?

Quasi-Newton updating

Consider the model

$$q(d; x_{k+1}, H_{k+1}) = f(x_{k+1}) + \nabla f(x_{k+1})^T d + \tfrac{1}{2} d^T H_{k+1} d.$$

Matching the gradients of f and m_{k+1} at x_k yields the secant equation

$$H_{k+1}(\nabla f(x_{k+1}) - \nabla f(x_k)) = x_{k+1} - x_k.$$

Minimizing changes in $\{H_k\}$ yields the well-known BFGS update.

Questions:

- Is BFGS effective within GS?
- Are we making the best use of info?
- Ill-conditioning: Bad or good?

Quasi-Newton updating (AGS-LBFGS)

Consider BFGS, but instead of updating between iterations, update during them.

- For each k, initialize $H_k \leftarrow \mu_k I$.
- Imagine moving along each $d_{ki} = x_{ki} - x_k$ and apply BFGS update.

With at most p points in the sample set, this is an L-BFGS-type approach.

Overestimation (AGS-over)

Suppose we also have function values at the sample points.

- Try to choose H_k so that the following model overestimates f:

$$q(d; X_k, H_k) = f(x_k) + \max_{x \in X_k} \{\nabla f(x)^T d\} + \tfrac{1}{2} d^T H_k d.$$

- If $q(d_{ki}; X_k, H_k) < f(x_{ki})$, then "lift" $d_{ki}^T H_k d_{ki}$ so that $q(d_{ki}; X_k, H_k) = f(x_{ki})$.
- Updates we use have the form $H_k \leftarrow M_{ki}^T H_k M_{ki}$ where

$$M_{ki} = \left(I + \frac{\gamma}{d_{ki}^T d_{ki}} d_{ki} d_{ki}^T \right).$$

Global convergence of AGS

Theorem: Let $\sigma, \gamma > 0$ be user-defined constants. Then, for any k, after all updates have been performed for AGS-LBFGS for sample points 1 through $p_k \leq p$, the following holds for any $d \in \mathbb{R}^n$:

$$\left(2^p\left(1+\frac{\sigma}{\gamma^2}\right)^p \mu_k + \frac{1}{\gamma}\left(\frac{2^p\left(1+\frac{\sigma}{\gamma^2}\right)^p - 1}{2\left(1+\frac{\sigma}{\gamma^2}\right)-1}\right)\right)^{-1} \|d\|^2 \leq d^T H_k d \leq \left(\mu_k + \frac{p\sigma}{\gamma}\right)\|d\|^2.$$

Theorem: Let $\rho \geq 1/2$ be a user-defined constant. Then, for any k, after all updates have been performed for AGS-over for sample points 1 through $p_k \leq p$, the following holds for any $d \in \mathbb{R}^n$:

$$\mu_k \|d\|^2 \leq d^T H_k d \leq \mu_k (2\rho)^p \|d\|^2.$$

Theorem: Let f be locally Lipschitz and continuously differentiable on an open dense $\mathcal{D} \subset \mathbb{R}^n$. Then, w.p.1, $f(x_k) \to -\infty$ or every cluster point of $\{x_k\}$ is stationary for f.

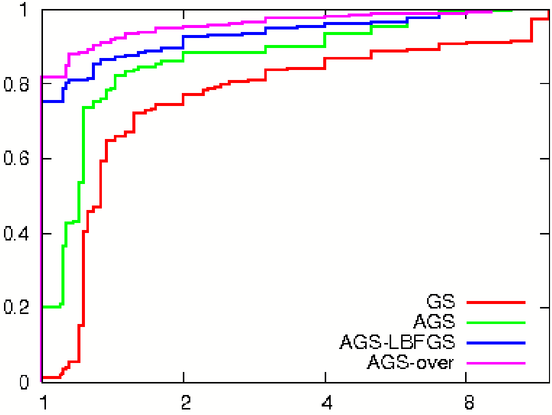
(See Curtis and Que (2011).)

Implementation and test details

- Matlab implementation
- QO solver adapted from Kiwiel (1986)
- 26 test problems from Haarala (2004) with $n = 50$
- Each problem run with 10 random starting points
- GS: $p = 2n$ gradients per iteration
- AGS: $p = 2n$ required for full line search, but only 5 gradients per iteration

Performance profile for final ϵ

Limit of 5000 gradient evaluations: GS, 49 iters.; AGS, 833 iters.



Final $\epsilon \in \{10^{-1}, \ldots, 10^{-12}\}$; performance profile for $\log_{10} \epsilon + 13$.

Outline

Nonlinear constrained optimization

Consider constrained optimization problems of the form:

$$\begin{aligned} \min_x \; & f(x) && \text{(smooth)} \\ \text{s.t. } & c_{\mathcal{E}}(x) = 0 && \text{(smooth)} \\ & c_{\mathcal{I}}(x) \leq 0 && \text{(smooth)} \end{aligned}$$

- Decades worth of algorithmic development.
- SQP, IPM, etc., with countless variations.
- Strong global and local convergence guarantees.
- Multiple popular, successful software packages.

Nonlinear constrained optimization with nonsmoothness

Consider constrained optimization problems of the form:

$$
\begin{aligned}
\min_{x}\ & f(x) && \text{((non)smooth)} \\
\text{s.t. } & c_{\mathcal{E}}(x) = 0 && \text{(smooth)} \\
& c_{\tilde{\mathcal{E}}}(x) = 0 && \text{(nonsmooth)} \\
& c_{\mathcal{I}}(x) \le 0 && \text{(smooth)} \\
& c_{\tilde{\mathcal{I}}}(x) \le 0 && \text{(nonsmooth)}
\end{aligned}
$$

- Algorithms for smooth problems no longer effective theoretically/practically.
- However, so much of the structure is the same as before.
- Can we adapt nonlinear optimization technology to handle nonsmoothness?

Constrained optimization with smooth functions

Consider constrained optimization problems of the form:

$$\begin{aligned} \min_x \ & f(x) && \text{(smooth)} \\ \text{s.t. } & c(x) \le 0 && \text{(smooth)} \end{aligned}$$

At x_k, solve the SQP subproblem

$$\begin{aligned} \min_d \ & f(x_k) + \nabla f(x_k)^T d + \tfrac{1}{2} d^T H_k d \\ \text{s.t. } & c(x_k) + \nabla c(x_k)^T d \le 0 \end{aligned}$$

to compute the search direction d_k.

Inconsistent linearizations of the constraints

The linearized constraints may be inconsistent, but we can relax the problem to

$$\begin{aligned} \min_{d,s} \ & \rho(f(x_k) + \nabla f(x_k)^T d) + e^T s + \tfrac{1}{2} d^T H_k d \\ \text{s.t. } & c(x_k) + \nabla c(x_k)^T d \le s, \quad s \ge 0, \end{aligned}$$

Solving the (P)SQP subproblem is equivalent to minimizing

$$q_\rho(d; x_k, H_k) := \rho(f(x_k) + \nabla f(x_k)^T d) + \sum \max\{c^i(x_k) + \nabla c^i(x_k)^T d, 0\} + \tfrac{1}{2} d^T H_k d.$$

We perform a line search on the exact penalty function

$$\phi_\rho(x) \triangleq \rho f(x) + \sum \max\{c^i(x), 0\}$$

to promote global convergence.

SQP method

for $k = 0, 1, 2, \ldots$

- Solve the SQP subproblem

$$\min_{d,s} \ \rho(f(x_k) + \nabla f(x_k)^T d) + e^T s + \tfrac{1}{2} d^T H_k d$$
$$\text{s.t. } c(x_k) + \nabla c(x_k)^T d \leq s, \quad s \geq 0$$

  to compute d_k.
- Backtrack from $\alpha_k \leftarrow 1$ to satisfy the sufficient decrease condition

$$\phi_\rho(x_k + \alpha_k d_k) \leq \phi_\rho(x_k) - \eta \alpha_k \Delta q_\rho(d_k; x_k, H_k).$$

- Update $x_{k+1} \leftarrow x_k + \alpha_k d_k$.

Constrained optimization of nonsmooth functions

Consider constrained optimization problems of the form

$$\begin{aligned} \min_x \ & f(x) && \text{(nonsmooth, locally Lipschitz)} \\ \text{s.t. } & c(x) \leq 0 && \text{(nonsmooth, locally Lipschitz)} \end{aligned}$$

We may consider applying an unconstrained technique (e.g., AGS) directly to

$$\min_x \ \phi_\rho(x),$$

but can we do better by maintaining the framework of SQP?

SQP and GS

- The SQP subproblem (for a smooth constrained problem) is

$$\begin{aligned}\min_{z,d,s}\ & \rho z + e^T s + \tfrac{1}{2} d^T H_k d \\ \text{s.t. } & f(x_k) + \nabla f(x_k)^T d \le z \\ & c(x_k) + \nabla c(x_k)^T d \le s,\ \ s \ge 0.\end{aligned}$$

- The AGS subproblem (for a nonsmooth objective) is

$$\begin{aligned}\min_{z,d}\ & z + \tfrac{1}{2} d^T H_k d \\ \text{s.t. } & f(x_k) + \nabla f(x)^T d \le z,\ \text{ for } x \in X_k.\end{aligned}$$

SQP and GS

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- The SQP-GS subproblem (for a nonsmooth constrained problem) is

$$\begin{aligned}\min_{z,d,s}\ & \rho z + e^T s + \tfrac{1}{2} d^T H_k d \\ \text{s.t.}\ & f(x_k) + \nabla f(x)^T d \le z,\ \text{ for } x \in X_k^f \\ & c^i(x_k) + \nabla c^i(x)^T d \le s^i,\ \ s^i \ge 0,\ \text{ for } x \in X_k^{c^i},\ \ i = 1, \ldots, m\end{aligned}$$

SQP-GS in more detail

- The SQP-GS subproblem is

$$\begin{aligned}
\min_{z,d,s}\ & \rho z + e^T s + \tfrac{1}{2} d^T H_k d \\
\text{s.t. } & f(x_k) + \nabla f(x)^T d \le z, \ \text{ for } x \in X_k^f \\
& c^i(x_k) + \nabla c^i(x)^T d \le s^i, \ s^i \ge 0, \ \text{ for } x \in X_k^{c^i}, \ i = 1, \dots, m
\end{aligned}$$

where X_k is composed of

$$\begin{aligned}
X_k^f &= \{x_k, x_{k1}^f, \dots, x_{kp}^f\} \subset \mathbb{B}_\epsilon(x_k) \cap \mathcal{D}^f \\
\text{and } X_k^{c^i} &= \{x_k, x_{k1}^{c^i}, \dots, x_{kp}^{c^i}\} \subset \mathbb{B}_\epsilon(x_k) \cap \mathcal{D}^{c^i} \text{ for } i = 1, \dots, m.
\end{aligned}$$

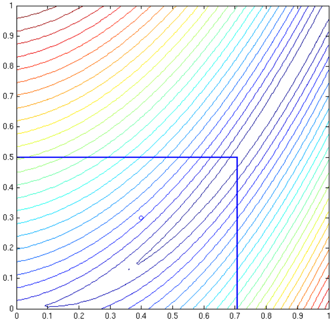
- This is equivalent to minimizing

$$q_\rho(d; X_k, H_k) :=$$

$$\rho \max_{x \in X_k^f} (f(x_k) + \nabla f(x)^T d) + \sum \max_{x \in X_k^{c^i}} \max\{c^i(x_k) + \nabla c^i(x)^T d, 0\} + \tfrac{1}{2} d^T H_k d.$$

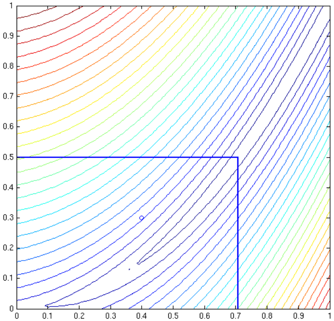
SQP-GS illustration

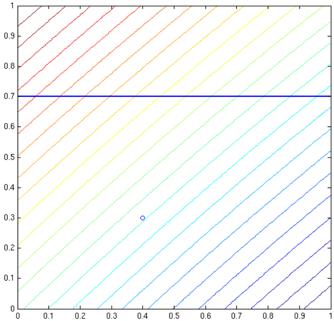
$$\min_x \; 10|x_2 - x_1^2| + (1 - x_1)^2 \quad \text{s.t.} \quad \max\{\sqrt{2}x_1, 2x_2\} - 1 \le 0 \quad \text{at } x_k = (\tfrac{2}{5}, \tfrac{3}{10}).$$



SQP-GS illustration

$$\min_x \; 10|x_2 - x_1^2| + (1-x_1)^2 \quad \text{s.t.} \quad \max\{\sqrt{2}x_1, 2x_2\} - 1 \leq 0 \quad \text{at } x_k = (\tfrac{2}{5}, \tfrac{3}{10}).$$





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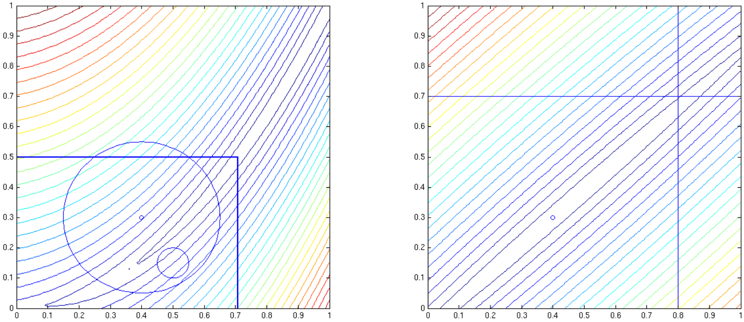


SQP-GS method

for $k = 0, 1, 2, \ldots$

- Sample $p \geq n+1$ points for each function to generate $X_k = \{X_k^f, X_k^{c^1}, \ldots, X_k^{c^m}\}$.
- Compute d_k by solving the SQP-GS subproblem

$$\begin{aligned}
\min_{z,d,s}\ & \rho z + e^T s + \tfrac{1}{2} d^T H_k d \\
\text{s.t. } & f(x_k) + \nabla f(x)^T d \leq z, \text{ for } x \in X_k^f \\
& c^i(x_k) + \nabla c^i(x)^T d \leq s^i,\ s^i \geq 0, \text{ for } x \in X_k^{c^i},\ i = 1, \ldots, m
\end{aligned}$$

- Backtrack from $\alpha_k \leftarrow 1$ to satisfy the sufficient decrease condition

$$\phi_\rho(x_k + \alpha_k d_k) \leq \phi_\rho(x_k) - \eta \alpha_k \Delta q_\rho(d_k; X_k, H_k).$$

- Update $x_{k+1} \approx x_k + \alpha_k d_k$ (to ensure $x_{k+1} \in \mathcal{D}^f \cap \mathcal{D}^{c^1} \cap \cdots \cap \mathcal{D}^{c^m}$)
- If $\Delta q_\rho(d_k; X_k, H_k) \leq \frac{1}{2}\epsilon^2$, then reduce ϵ.
- If ϵ has been reduced and x_k is not sufficiently feasible, then reduce ρ.

Convergence theory for SQP-GS

Theorem: Suppose the following conditions hold:

- f and c^i, $i = 1, \ldots, m$, are locally Lipschitz and continuously differentiable on open dense subsets of $\mathbb{R}^n$.
- $\{x_k\}$ and all generated sample points are contained in a convex set over which f and c^i, $i = 1, \ldots, m$, and their first derivatives are bounded.
- $\{H_k\}$ are symmetric positive definite, bounded above in norm, and bounded away from singularity.

Then, w.p.1, one of the following holds true:

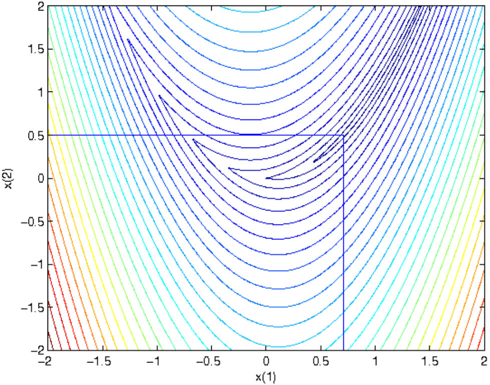
- $\rho = \rho_* > 0$ for all large k and every cluster point of $\{x_k\}$ is stationary for ϕ_{ρ_*}. Moreover, with K defined as the infinite subsequence of iterates during which ϵ is decreased, all cluster points of $\{x_k\}_{k \in K}$ are feasible for the optimization problem.
- $\rho \to 0$ and every cluster point of $\{x_k\}$ is stationary for ϕ_0.

Implementation

- Matlab implementation
- QO subproblems solved with MOSEK
- BFGS approximations of Hessian of $\phi_\rho(x)$ (as in AGS-LBFGS)
- $p = 2n$ gradients per iteration

Example 1: Nonsmooth Rosenbrock

$$\min_{x} \; 10|x_1^2 - x_2| + (1 - x_1)^2 \quad \text{s.t.} \;\; \max\{\sqrt{2}x_1, 2x_2\} \leq 1.$$



Example 1: Nonsmooth Rosenbrock

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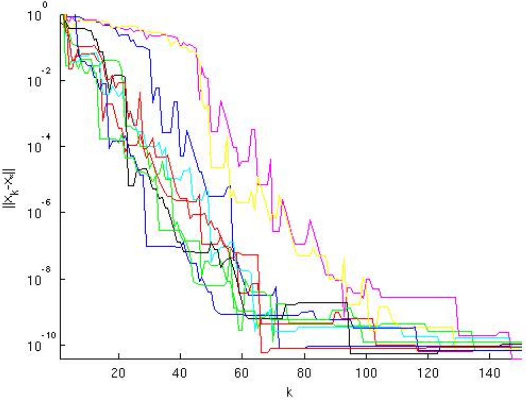

Plot of distance to solution

Example 1: Nonsmooth Rosenbrock

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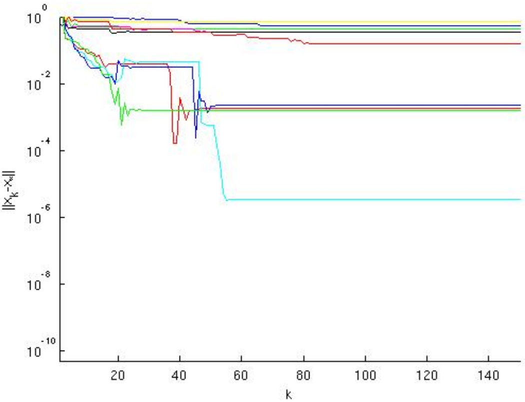


Plot of distance to solution (no sampling)

Example 2: Entropy minimization

Find a $N \times N$ matrix X that solves

$$\min_X \ \ln \left(\prod_{j=1}^{K} \lambda_j (A \circ X^T X) \right)$$
$$\text{s.t. } \|X_j\| = 1, \ j = 1, \ldots, N$$

where $\lambda_j(M)$ denotes the jth largest eigenvalue of M, A is a real symmetric $N \times N$ matrix, $\circ$ denotes the Hadamard matrix product, and X_j denotes the jth column of X.

Example 2: Entropy minimization

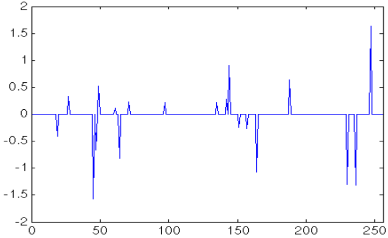
N	K	n	Objective	Infeasibility	Final ϵ	Opt. error
2	1	4	1.0000e+00	3.1752e-14	5.9605e-09	7.6722e-12
4	2	16	7.4630e-01	2.8441e-07	4.8828e-05	1.1938e-04
6	3	36	6.3359e-01	2.1149e-06	9.7656e-05	8.7263e-02
8	4	64	5.5832e-01	2.0492e-05	9.7656e-05	2.7521e-03
10	5	100	2.1841e-01	9.8364e-06	7.8125e-04	9.6041e-03
12	6	144	1.2265e-01	1.8341e-04	7.8125e-04	6.0492e-03
14	7	196	8.4650e-02	1.6692e-04	7.8125e-04	7.1461e-03
16	8	256	6.5051e-02	6.4628e-04	1.5625e-03	3.1596e-03

Example 3: $\ell_{0.5}$ norm minimization

Recover a sparse signal by solving

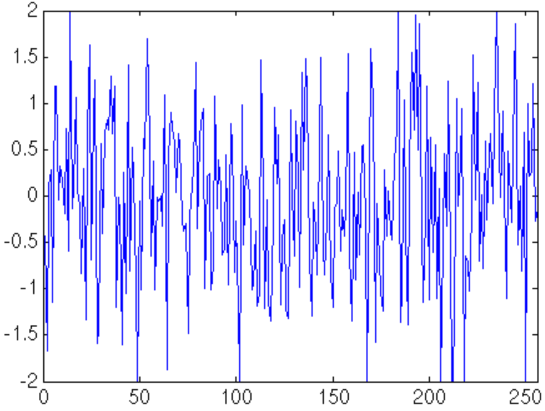
$$\begin{aligned} \min_x \ & \|x\|_{0.5} \\ \text{s.t. } & Ax = b \end{aligned}$$

where A is a 64×256 submatrix of a discrete cosine transform (DCT) matrix.



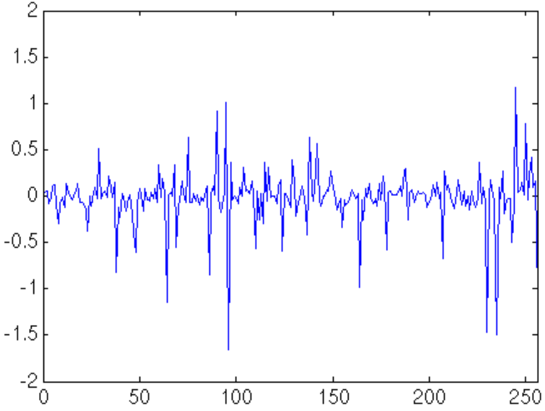
(Use $\ell_{0.5}$ norm as ℓ_1 does not recover sparse solution.)

Example 3: $\ell_{0.5}$ norm minimization



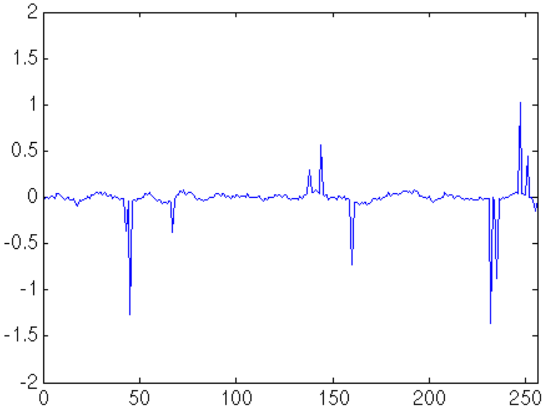
$k = 1$

Example 3: $\ell_{0.5}$ norm minimization



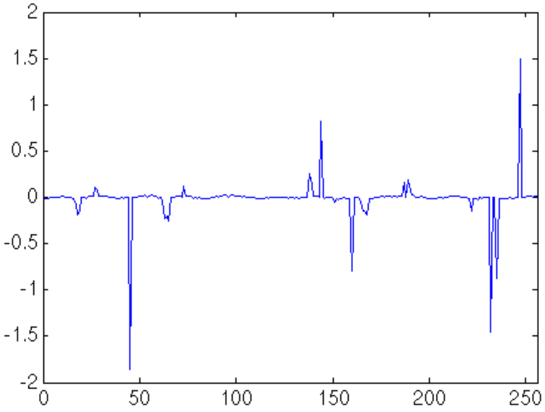
$k = 10$

Example 3: $\ell_{0.5}$ norm minimization



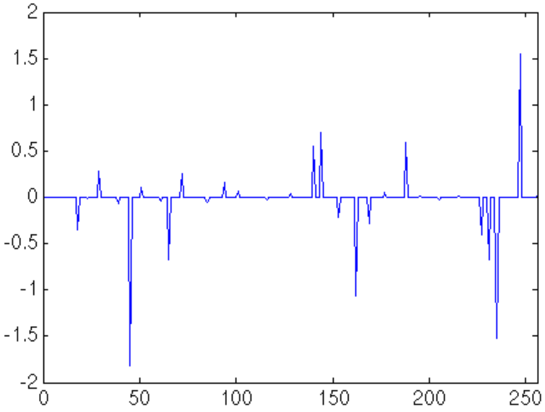
$k = 25$

Example 3: $\ell_{0.5}$ norm minimization



$k = 50$

Example 3: $\ell_{0.5}$ norm minimization



$k = 200$

Example 4: Robust optimization

Find the robust minimizer of a linear objective s.t. an uncertain quadratic constraint:

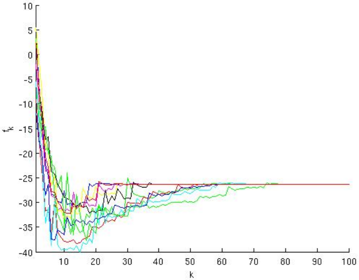
$$\min_x \; f^T x \quad \text{s.t.} \; x^T A x + b^T x + c \leq 0, \; \forall (A, b, c) \in \mathcal{U},$$

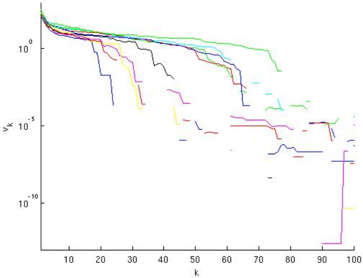
where $f \in \mathbb{R}^n$ and for each (A, b, c) in the uncertainty set

$$\mathcal{U} := \left\{ (A, b, c) : (A, b, c) = (A^{(0)}, b^{(0)}, c^{(0)}) + \sum_{i=1}^{10} u^i (A^{(i)}, b^{(i)}, c^{(i)}), \; u^T u \leq 1 \right\}$$

$A \in \mathbb{R}^{n \times n}$ is positive semidefinite, $b \in \mathbb{R}^n$, and $c \in \mathbb{R}$.

Example 4: Robust optimization





Plot of function values (left) and constraint violation values (right)

Outline

Summary

We set out to improve the practicality and enhance GS methods.

- We aimed to reduce overall gradient evaluations.
- We aimed to reduce the cost of the subproblem solves.
- We aimed to maintain convergence guarantees.
- We aimed to extend the methodology to constrained optimization.

The first goals can be achieved with adaptive sampling and Hessian approximations:

- $O(1)$ gradient evaluations required per iteration
- Subproblem solver warm-started effectively
- Hessian updating schemes improve performance
- Global convergence guarantees maintained

Last goal can be achieved in a SQP-GS framework with constraint gradient sampling:

- Subproblem solve is still a QO per iteration
- Global convergence guarantees maintained

Future work

- C++ implementation
- Tailored QO solver for constrained case
- Adaptive sampling in constrained case
- Special handling of partly smooth functions
- Merge with bundle techniques for convex problems

Thanks!

- F. E. Curtis and X. Que, "An Adaptive Gradient Sampling Algorithm for Nonsmooth Optimization," in 2^{nd} review for *Optimization Methods and Software*.
- F. E. Curtis and M. L. Overton, "A Sequential Quadratic Programming Method for Nonconvex, Nonsmooth Constrained Optimization," to appear in *SIAM Journal on Optimization*.