

INTRODUCTION

We aim to solve

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

where f is smooth but **its gradient is not available**.

Direct-search algorithms are derivative-free methods that are based on the exploration of the space through the use of *direction* or *polling sets*. Classic direct-search schemes require these sets to be **Positive Spanning Sets (PSS)**, i.e. sets that generate \mathbb{R}^n by positive linear combination. We study here how this assumption can be replaced while using random directions, thus leading to cheaper computations.

ALGORITHM

1. **Initialization:** Choose $x_0 \in \mathbb{R}^n$, $\alpha_0 > 0$, $\theta < 1 \leq \gamma$ and $\rho(t) = o(t)$ when $t \searrow 0$.

2. For $k = 0, 1, 2, \dots$

- Choose a set D_k of m unitary vectors.
- If it exists $d_k \in D_k$ so that

$$f(x_k + \alpha_k d_k) < f(x_k) - \rho(\alpha_k),$$

then set $x_{k+1} := x_k + \alpha_k d_k$ and update $\alpha_{k+1} := \gamma \alpha_k$.

- Otherwise set $x_{k+1} := x_k$ and update $\alpha_{k+1} := \theta \alpha_k$.

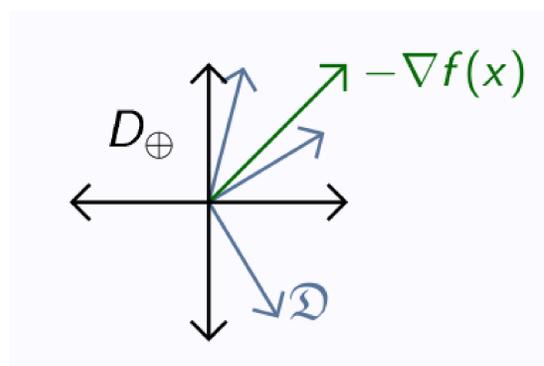
Remarks:

- * When D_k is a random set \mathcal{D}_k , it implies that the iterates x_k become random vectors X_k .
- * In the rest, $\rho(t) = ct^2$ with $c > 0$.

REFERENCES

- [1] S. Gratton, C. W. Royer, L. N. Vicente, and Z. Zhang. Direct search using probabilistic descent. Technical Report 14-11, Dept. Mathematics, Univ. Coimbra, 2014.
- [2] A. S. Bandeira, K. Scheinberg, and L. N. Vicente. Convergence of trust-region methods based on probabilistic models. Technical Report 13-11, Dept. Mathematics, Univ. Coimbra, 2013.
- [3] L. N. Vicente. Worst Case Complexity of Direct Search. *EURO Journal on Computational Optimization*, 1:143–153, 2013.

THEORETICAL RESULTS



Probabilistic descent

We say that a sequence $\{\mathcal{D}_k\}_k$ is p -probabilistically κ -descent (or (p, κ) -descent) if

$$\mathbb{P}(E_0) \geq p \quad \text{and} \quad \forall k \geq 1, \mathbb{P}(E_k | S_{k-1}) \geq p,$$

where

$$E_k = \left\{ \max_{d \in \mathcal{D}_k} \frac{-d^T \nabla f(X_k)}{\|\nabla f(X_k)\|} > \kappa \right\}$$

and S_{k-1} is the σ -algebra generated by the previous random sets $\mathcal{D}_0, \dots, \mathcal{D}_{k-1}$.

Convergence theorem

Using a p -probabilistic κ -descent set sequence with $p > \ln \theta / \ln(\gamma^{-1} \theta)$, one can show that

$$\mathbb{P} \left(\liminf_{k \rightarrow \infty} \|\nabla f(X_k)\| = 0 \right) = 1.$$

Worst-case complexity results

Let N_ϵ the number of function evaluations needed to obtain $\|\nabla f(X_k)\| \leq \epsilon \in (0, 1)$, then:

$$\mathbb{P}(N_\epsilon \leq \mathcal{O}(m \kappa^{-2} \epsilon^{-2})) \geq 1 - \exp(-\mathcal{O}(\epsilon^{-2})).$$

- For PSS, $p = 1$, $m \geq n + 1$, $\kappa \geq 1/\sqrt{n}$, and we recover the deterministic rate in $\mathcal{O}(n^2 \epsilon^{-2})$;
- For uniformly random sets of size m , this reduces to $\mathcal{O}(m n \epsilon^{-2})$ with overwhelming probability.

High probability iteration complexity

For ϵ sufficiently small and $P \in (0, 1)$, it holds

$$\mathbb{P} \left(\min_{0 \leq l \leq k} \|\nabla f(X_l)\| \leq \epsilon \right) \geq P \quad \text{whenever} \quad k \geq \mathcal{O}(\kappa^{-2} \epsilon^{-2}) - \mathcal{O}(\ln(1 - P)).$$

The interest of PSS is to provide at least one vector that makes an acute angle with the negative gradient, hence is a descent direction. However, being a PSS is not necessary to obtain this property.

The figure on the left shows that the PSS D_\oplus does not approximate the negative gradient as well as \mathcal{D} , although this set is clearly not a PSS.

NUMERICAL EXPERIMENTS

Problem	Dim	Set choice 1	Set choice 2
arglina	40	6.35	1.00
arglina	100	18.00	1.00
dqrtc	40	28.32	1.00
dqrtc	100	failed	1.00
vardim	40	2.97	1.00
vardim	100	8.04	1.00

Table 1: Ratio of function evaluations

The tolerance is 10^{-3} , $\rho(t) = 10^{-3} t^2$. The problems are from the CUTER package. The ratio corresponds to a mean on 100 runs. At iteration k , there are two different choices for the polling set:

1. A PSS of the form $[Q_k - Q_k]$ with Q_k orthogonal, $\gamma = 1$;
2. Two random directions i.i.d. uniformly distributed on the unit sphere, $\gamma = 2$.

Further improvements

- Using $[d - d]$ with d random is the best choice in terms of sets with two directions.
- Other probability distributions may lead to better results.

CONCLUSIONS

- Direct search can be proven convergent without the use of PSS.
- Using (p, κ) -descent sets reduces both theoretical complexity and numerical cost.
- The reasoning for global rates can be used for other algorithms (already applied to a trust-region framework).
- Future work: extending these results to the nonsmooth/convex cases.

ACKNOWLEDGMENTS

Support for this research was provided by FCT under grants PTDC/MAT/116736/2010 and PESt-C/MAT/UI0324/2011 and by RTRA under the grant ADTAO.