Opportunism and ordering strategies in derivative-free optimization

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Presentation Outline

1. What are Derivative-Free and Blackbox Optimization?
2. Direct-search Methods
3. Opportunism and ordering
4. Numerical results

Derivative-Free and Blackbox Optimization

Optimization problem :

$$\begin{cases} \min\limits_{x \in \mathbb{R}^n} & f(x) \\ \text{s.à.} & c_j(x) \leq 0 \quad \forall j \in \{1, \dots, m\} \\ & l_i \leq x_i \leq u_i \quad \forall i \in \{1, \dots, n\} \end{cases}$$

Derivative-Free and Blackbox Optimization

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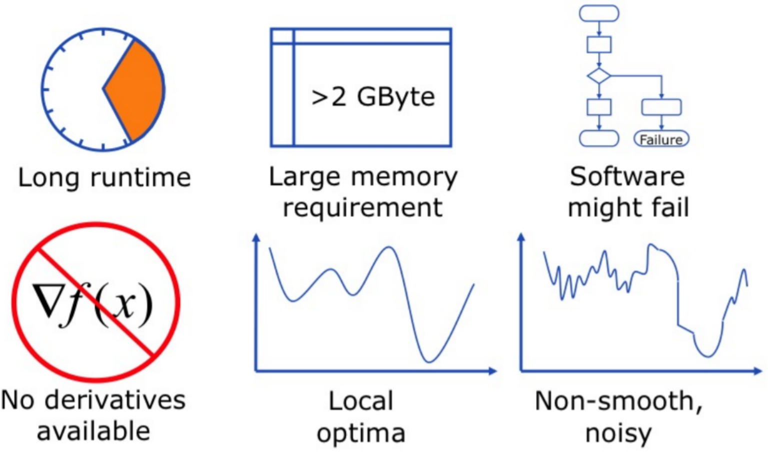
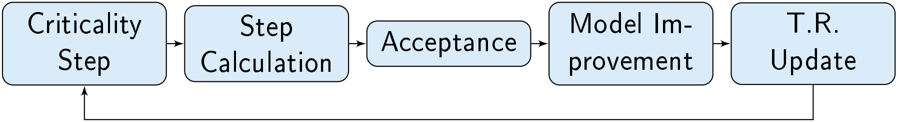
- $f(x)$ and $c_j(x)$ are treated as blackboxes.

Blackbox


>2 GByte
Failure
Long runtime
Large memory requirement
Software might fail
$\nabla f(x)$
No derivatives available
Local optima
Non-smooth, noisy

DFO and BBO methods

Trust Region Methods



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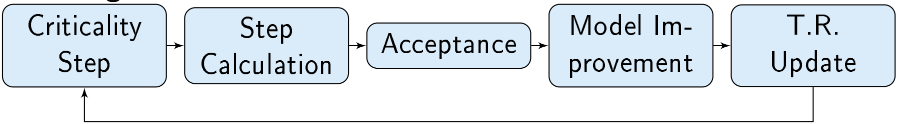
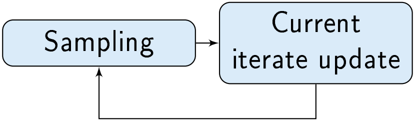


Direct-search Methods



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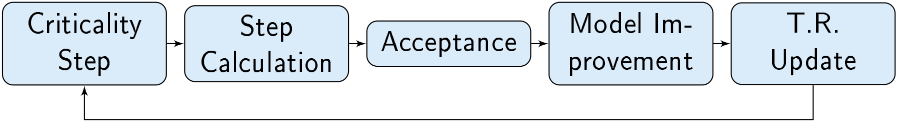

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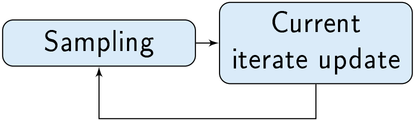

Directional (MADS)

DFO and BBO methods

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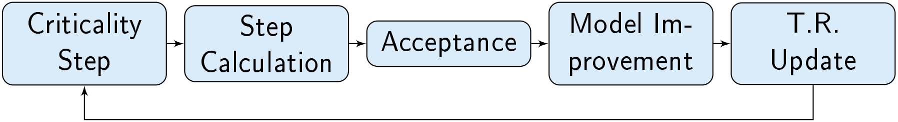

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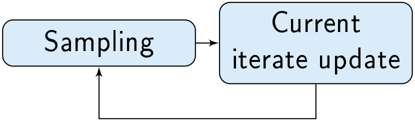

Directional (MADS)

Simplicial (Nelder-Mead)

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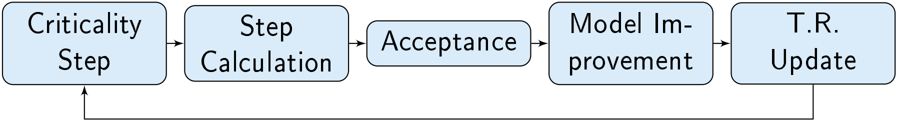

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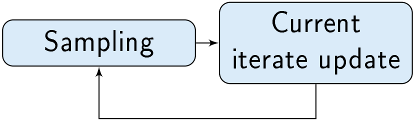

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Other methods

DFO and BBO methods

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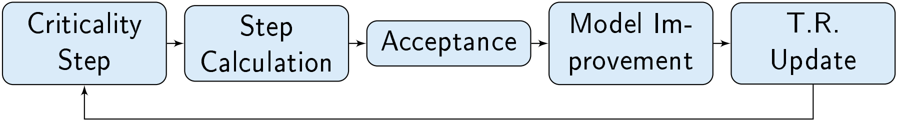

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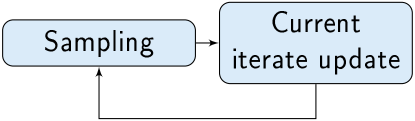

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Heuristics (Particle Swarm, Simulated Annealing)

DFO and BBO methods

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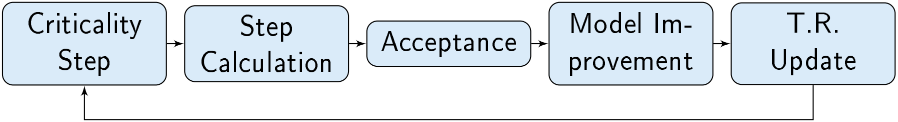

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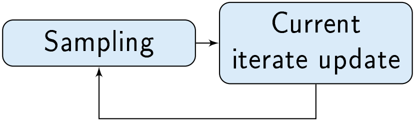

Directional (MADS)

Simplicial (Nelder-Mead)

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Heuristics (Particle Swarm, Simulated Annealing)

Hybrids (Implicit Filtering)

What Are We Trying to Achieve?

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The opportunistic strategy designates the premature termination of an algorithmic step as soon as the necessary conditions to proceed to the next step are met.

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Opportunistic Strategy

The opportunistic strategy designates the premature termination of an algorithmic step as soon as the necessary conditions to proceed to the next step are met.

Often mentionned but never studied per se.

Identifying suitable methods

Question 1.

For which methods is the opportunistic strategy applicable?

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- Allows opportunistic termination.

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Heuristics ?

- Highly dependent on the heuristic.

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- Samples $f(x)$ and $c(x)$ on $\mathcal{L}^k$, a list of point specific to the k^{th} iteration.

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Algorithm 1 Direcitonal direct-search framework

for $k = 1, 2, \ldots$ **do**
  Search : Evaluate $f(x)$ at a finite set of point S^k.
  If successful, update x^k

  Poll : Evaluate $f(x)$ at a finite set of point
  $P^k := \{x^k + \delta^k d : d \in D\}$, where D is a positive spanning set of **directions**.
  If successful, update x^k and mesh parameters.
end for

Remark : this work only encompasses the study of the impact of the opportunistic strategy on poll steps.

Coordinate Search (CS)

Algorithm 2 Coordinate Search

for $k = 1, 2, \ldots$ **do**

  Poll : Evaluate $f(x)$ at
  $P^k := \{x^k + \delta^k d : d \in D_\oplus\}$, where
  $D_\oplus := \{\pm e_1, \pm e_2, \ldots, \pm e_n\}$.

  If $\exists\ t$ for which $f(t) < f(x^k)$, $t \in P^k$
  Successful step
  update $x^{k+1} \leftarrow t$ et $\delta^{k+1} \leftarrow \delta^k$.

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  Unsuccessful step
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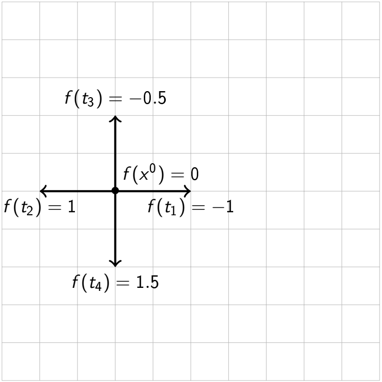
end for



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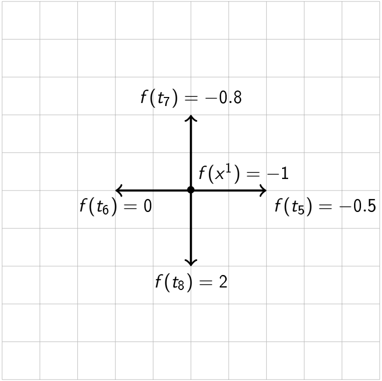

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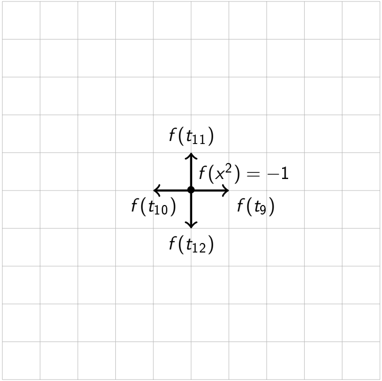

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Generalized Pattern Search (GPS)

Algorithm 3 Generalized Pattern Search

for $k = 1, 2, \dots$ **do**

with $\tau \in \{0, 1\}$.

Poll : Evaluate $f(x)$ at $P^k := \{x^k + \delta^k d : d \in D\}$, where D is a positive spanning set.

If $\exists\ t$ for which $f(t) < f(x^k)$, $t \in P^k$

Successful step

update $x^{k+1} \leftarrow t$ et $\delta^{k+1} \leftarrow \tau^{-1}\delta^k$.

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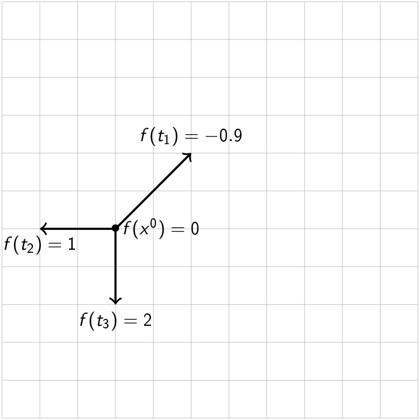

Figure: GPS

Generalized Pattern Search (GPS)

Algorithm 4 Generalized Pattern Search

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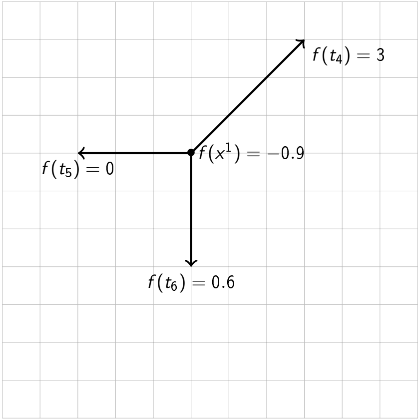

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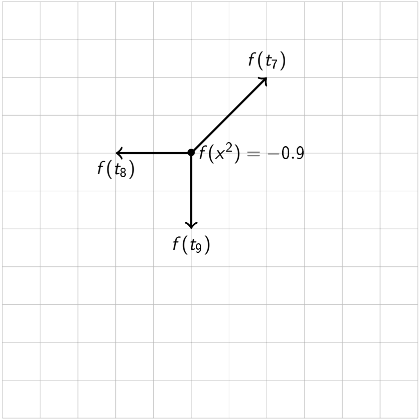

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Generating Set Search (GSS)

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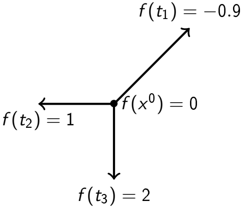

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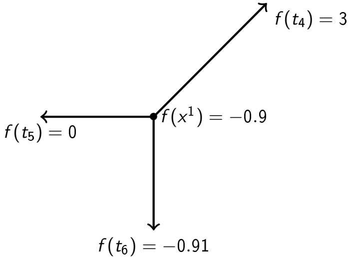

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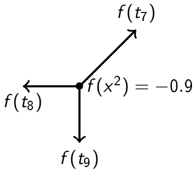

Figure: GSS

Mesh Adaptive Direct Search (MADS)

Algorithm 5 Mesh Adaptive Direct Search

for $k = 1, 2, \ldots$ **do**
with $\tau \in \{0, 1\}$.
Update : $\delta^k \leftarrow \min(\Delta^k, (\Delta^k)^2)$
Poll : Evaluate $f(x)$ at
$P^k := \{x^k + \delta^k d : d \in D\}$, where
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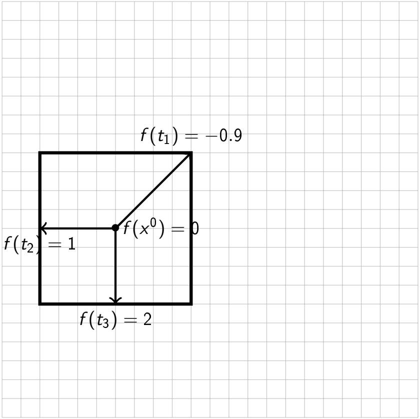

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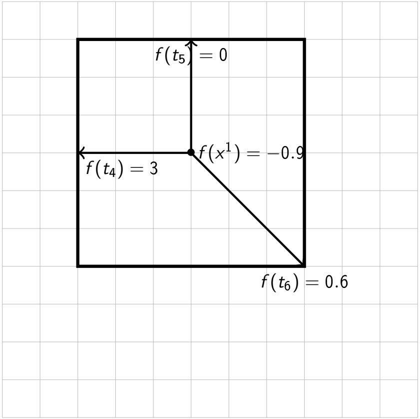

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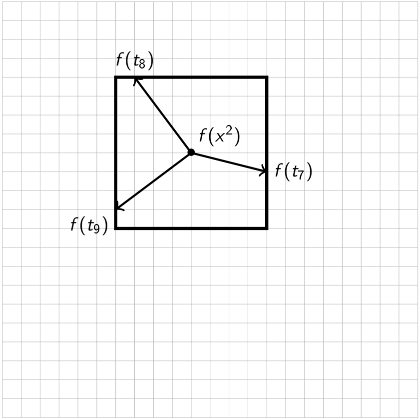

Figure: MADS

Implicit Filtering (IMFIL)

Algorithm 6 Implicit Filtering

for $k = 1, 2, \ldots$ **do**

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If $\exists\ t$ for which $f(t) < f(x^k)$, $t \in P^k$
Successful step
Line search following $-\nabla_s f(x^k)$.
update $x^{k+1} \leftarrow t$ et $\delta^{k+1} \leftarrow \delta^k$.

Else $\nexists\ t$ for which $f(t) < f(x^k)$, $t \in P^k$
Unsuccessful step
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end for

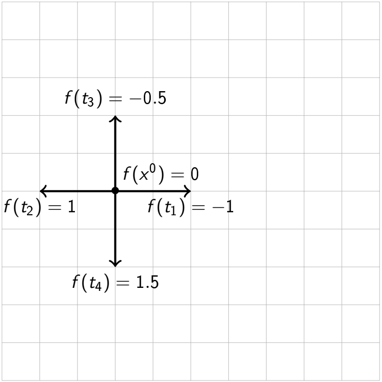

Figure: IMFIL

Implicit Filtering (IMFIL)

Algorithm 6 Implicit Filtering

for $k = 1, 2, \ldots$ **do**

Poll : Evaluate $f(x)$ at $P^k := \{x^k + \delta^k d : d \in D_\oplus\}$, where $D_\oplus := \{\pm e_1, \pm e_2, \ldots, \pm e_n\}$.

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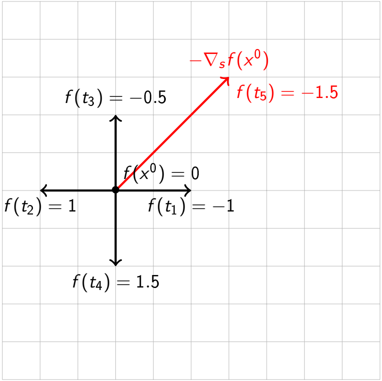

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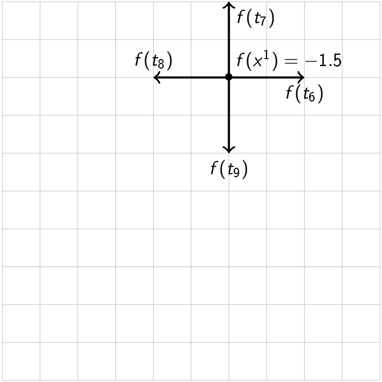

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Opportunistic strategies

Complete polling

Designates the evaluation of $f(x)$ and $c(x)$ at every point generated in the poll step.

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Ordering strategies

Ordering strategy

Rule guiding the ordering of points in a set $\mathcal{L}$.

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No practical use, for comparaison only.

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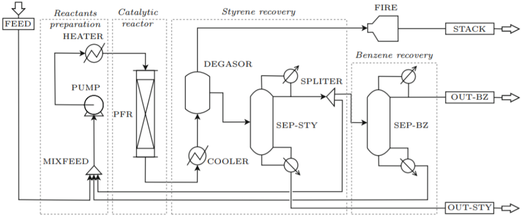

Figure: Styrene production chart [?]

Opportunistic strategies comparison

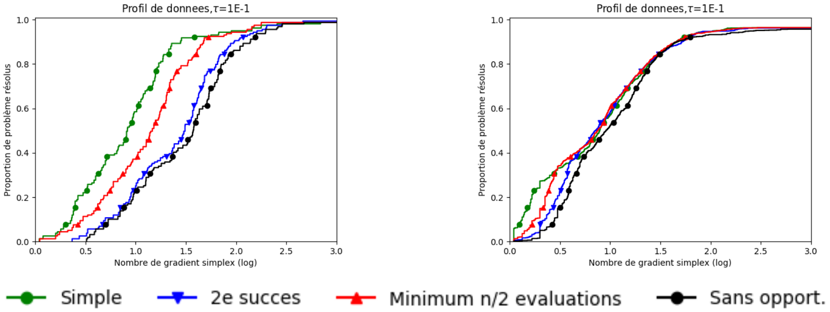

Figure: Left : CS on Moré-Wild, Right MADS on Moré-Wild

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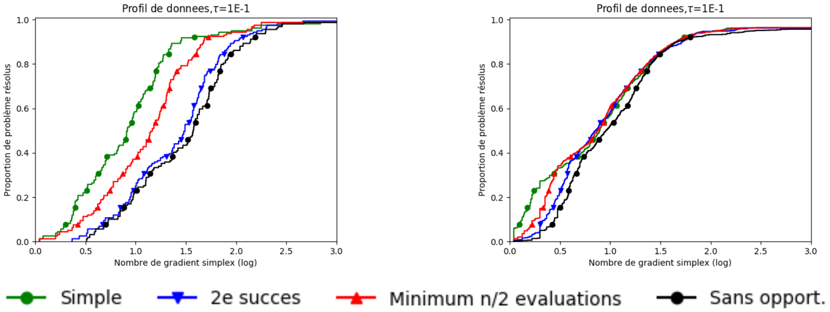

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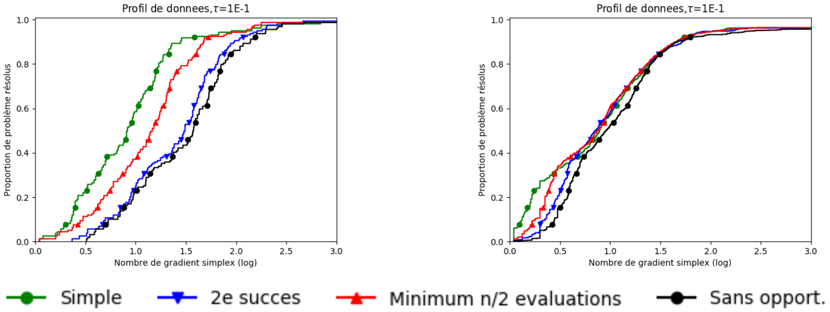

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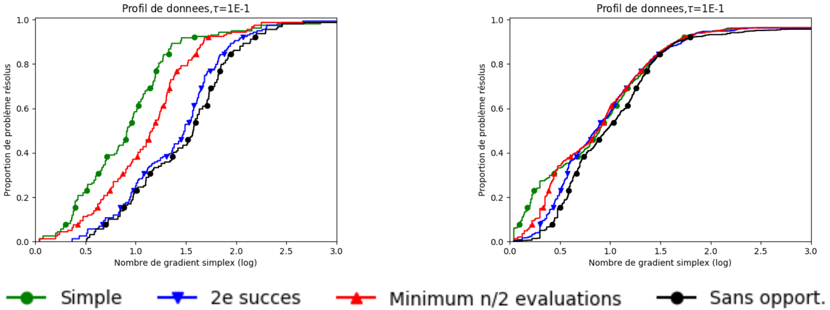

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3. Impact less important on MADS.

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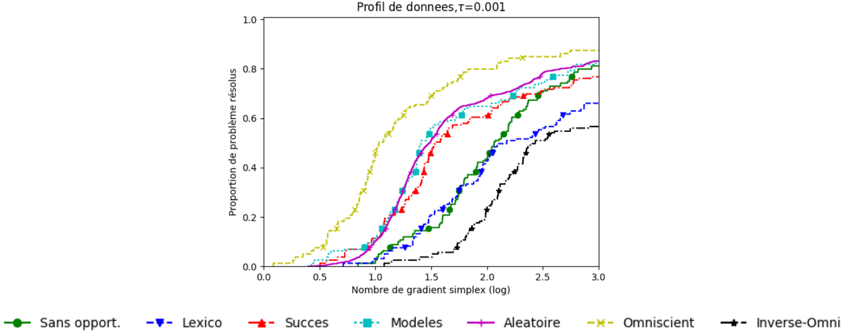

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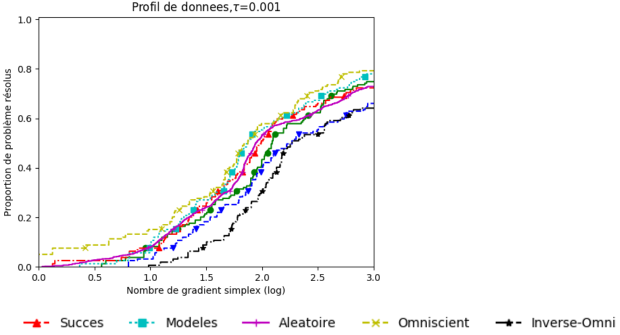

Figure: GPS on Moré-Wild

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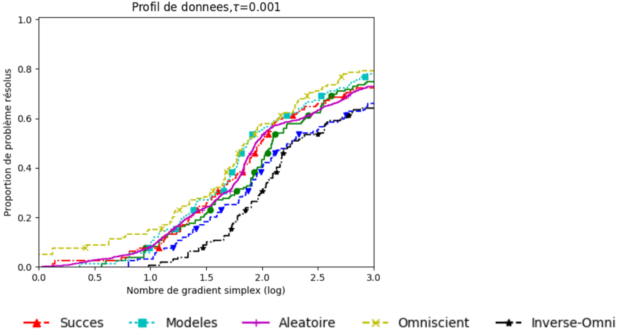

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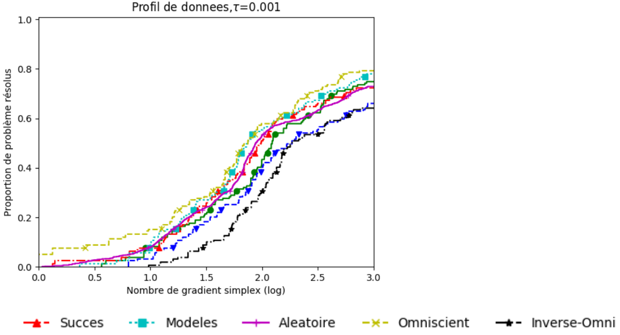

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