Opportunism and ordering strategies in derivative-free optimization

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Presentation Outline

Derivative-Free and Blackbox Optimization

Optimization problem :

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

Derivative-Free and Blackbox Optimization

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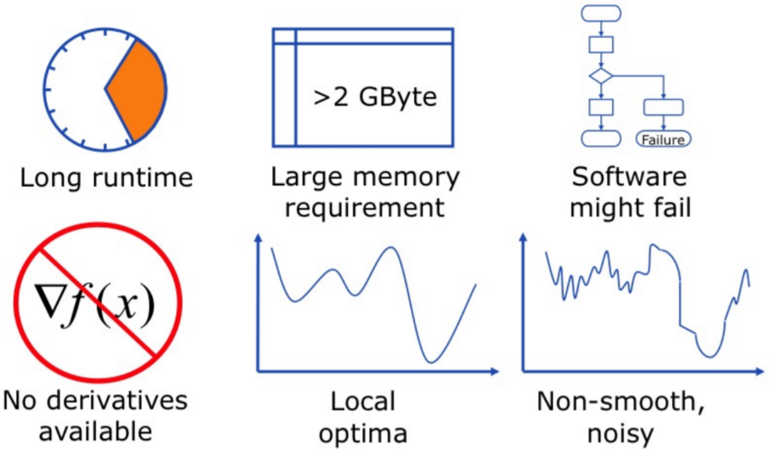
- $f(x)$ and $c_j(x)$ are treated as blackboxes.

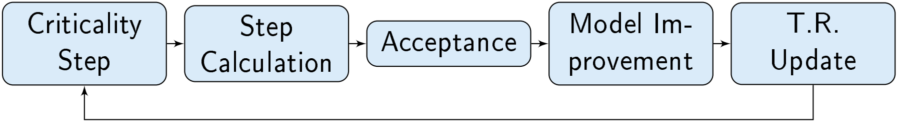
Blackbox



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

DFO and BBO methods

Trust Region Methods



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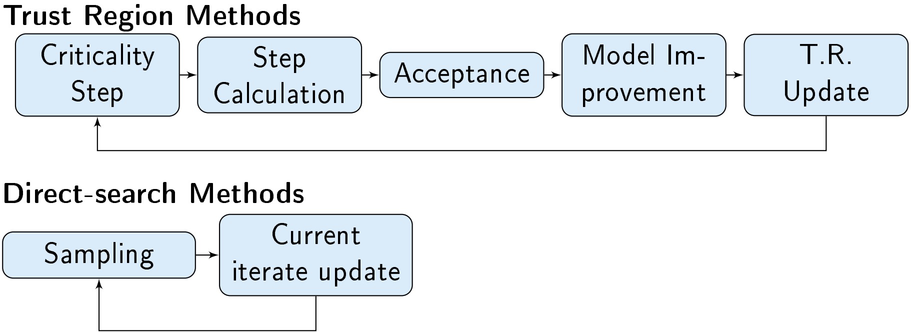

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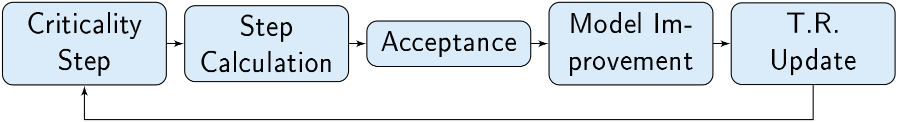
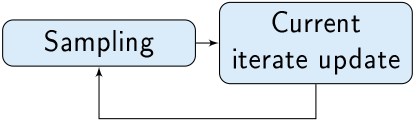


Direct-search Methods



Directional (MADS)

DFO and BBO methods

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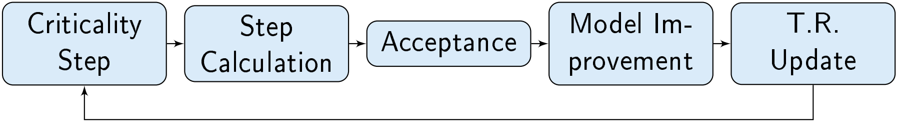

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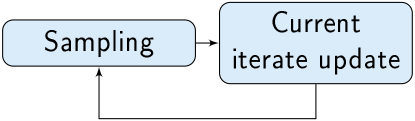

Directional (MADS)

Simplicial (Nelder-Mead)

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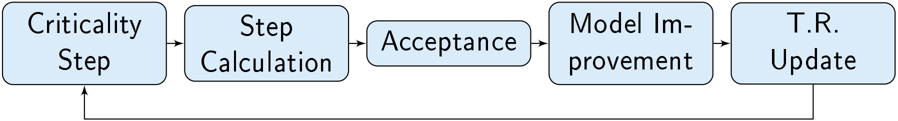

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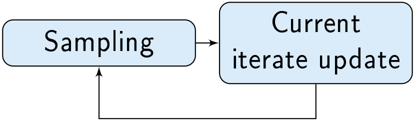

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DFO and BBO methods

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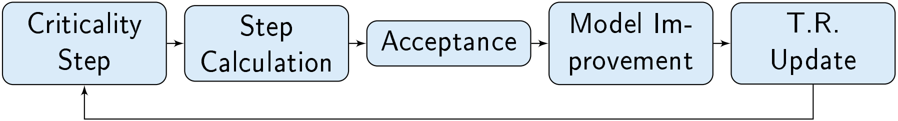

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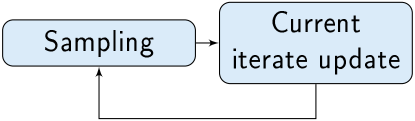

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Heuristics (Particle Swarm, Simulated Annealing)

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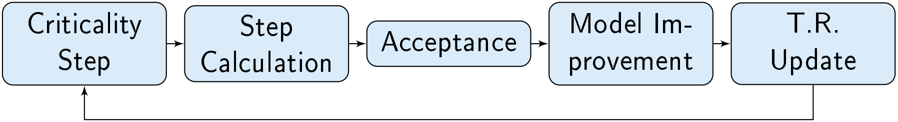

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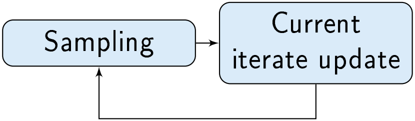

Directional (MADS)

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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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 $k = 1, 2, \dots$ **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 $\delta^{k+1} \leftarrow \delta^k$.

Else $\nexists\ t$ for which $f(t) < f(x^k)$, $t \in P^k$
Unsuccessful step
update $x^{k+1} \leftarrow x^k$ et $\delta^{k+1} \leftarrow \frac{\delta^k}{2}$.

end for

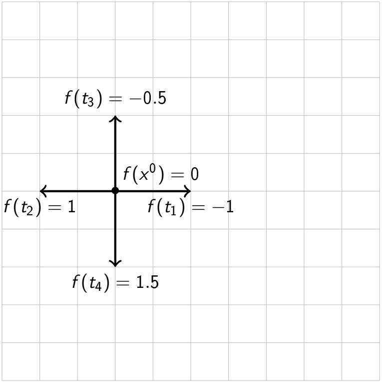

Figure: CS

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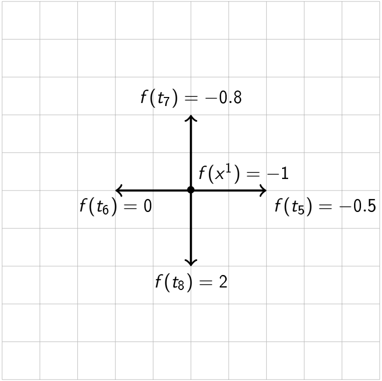

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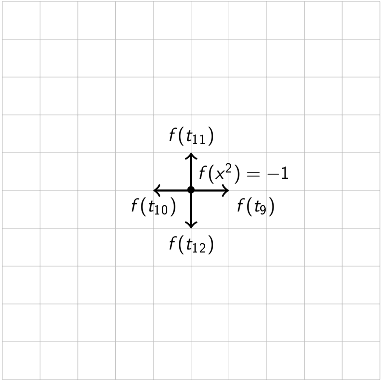

Figure: CS

Generalized Pattern Search (GPS)

Algorithm 3 Generalized Pattern Search

for $k = 1, 2, \ldots$ **do**
  with $\tau \in \{0, 1\}$.
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  $P^k := \{x^k + \delta^k d : d \in D\}$, where
  D is a positive spanning set.

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

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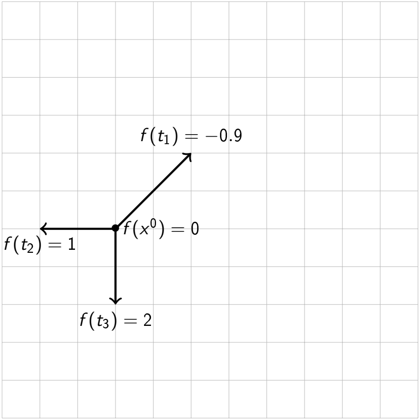

Figure: GPS

Generalized Pattern Search (GPS)

Algorithm 4 Generalized Pattern Search

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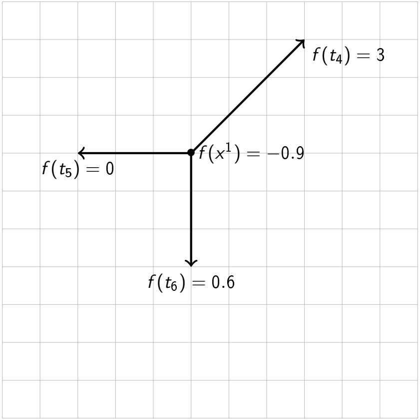

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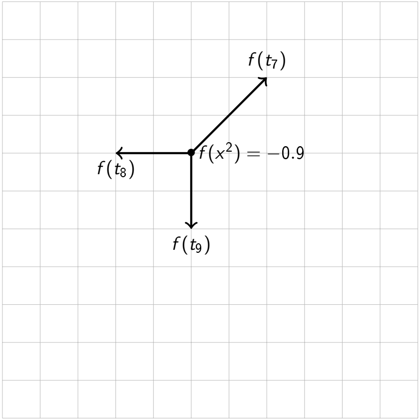

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Generating Set Search (GSS)

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  Poll : Evaluate $f(x)$ at
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  D is a positive spanning set
  respecting multiple conditions.

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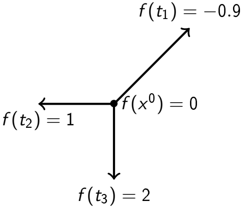

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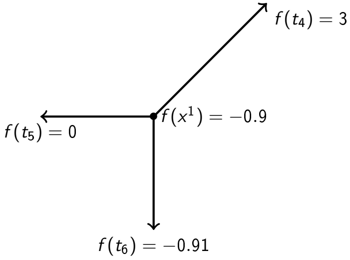

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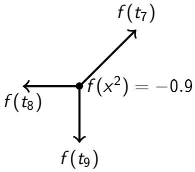

Figure: GSS

Mesh Adaptive Direct Search (MADS)

Algorithm 5 Mesh Adaptive Direct Search

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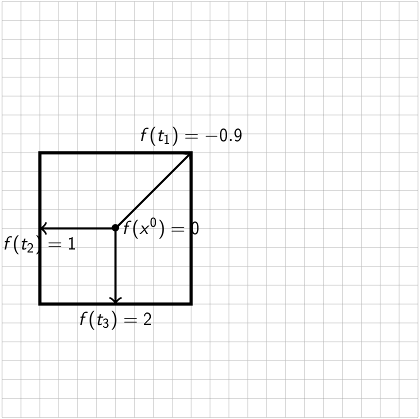

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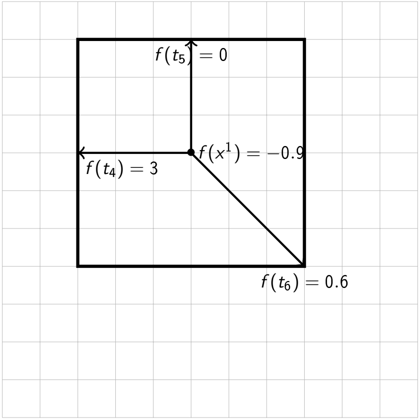

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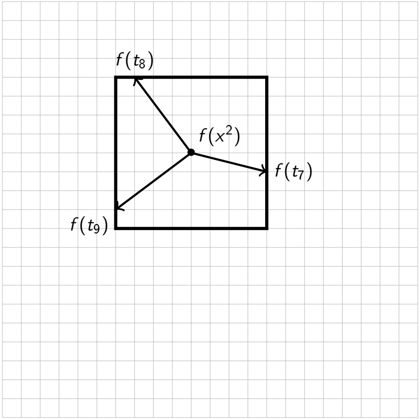

Figure: MADS

Implicit Filtering (IMFIL)

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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 $\delta^{k+1} \leftarrow \delta^k$.

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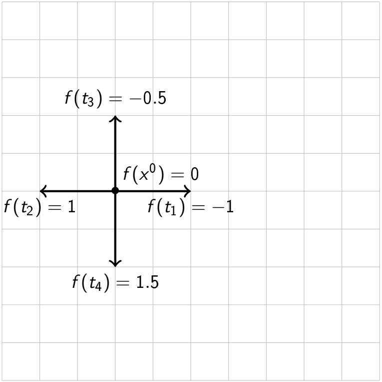

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If $\exists\ t$ for which $f(t) < f(x^k)$, $t \in P^k$
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Line search following $-\nabla_s f(x^k)$.
update $x^{k+1} \leftarrow t$ et $\delta^{k+1} \leftarrow \delta^k$.

Else $\nexists\ t$ for which $f(t) < f(x^k)$, $t \in P^k$
Unsuccessful step
update $x^{k+1} \leftarrow x^k$ et $\delta^{k+1} \leftarrow \frac{\delta^k}{2}$.

end for

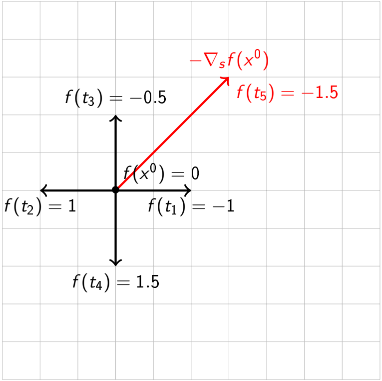

Figure: IMFIL

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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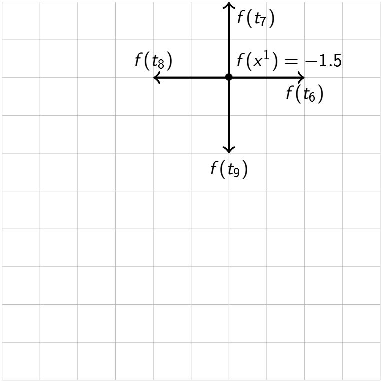

Figure: IMFIL

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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Opportunistic strategy after q evaluations

Opportunistic termination of the poll following the evaluations of q points.

Ordering strategies

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

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No practical use, for comparaison only.

Test problems

1. 212 instances of problems taken from [J.J. Moré and S.M. Wild 2009]

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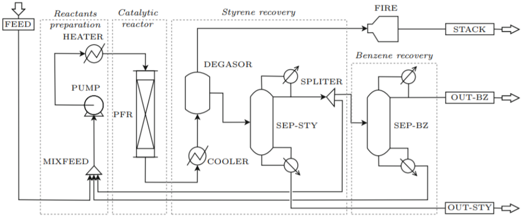

Figure: Styrene production chart [Audet, Béchard, Le Digabel 2008]

Opportunistic strategies comparison

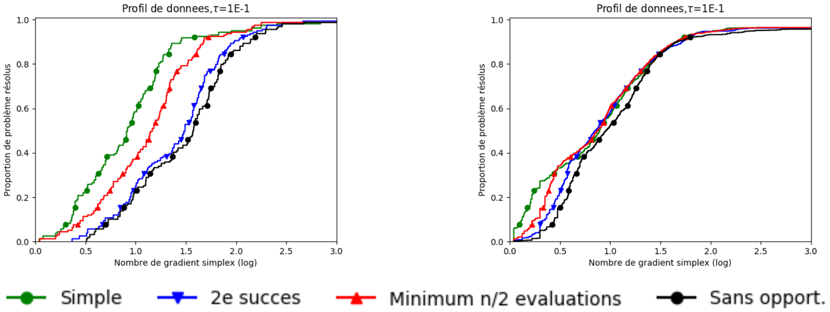

Figure: Left : CS on Moré-Wild, Right MADS on Moré-Wild

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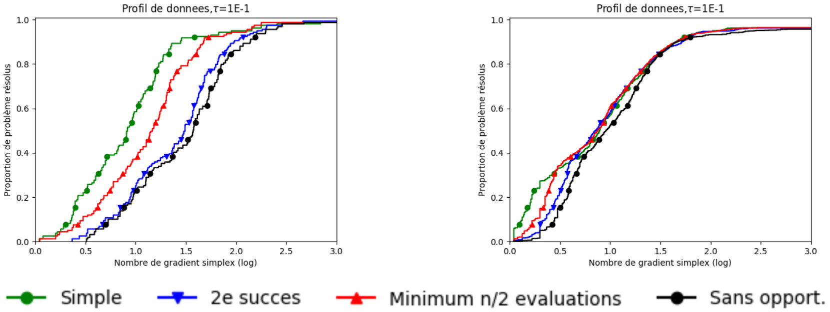

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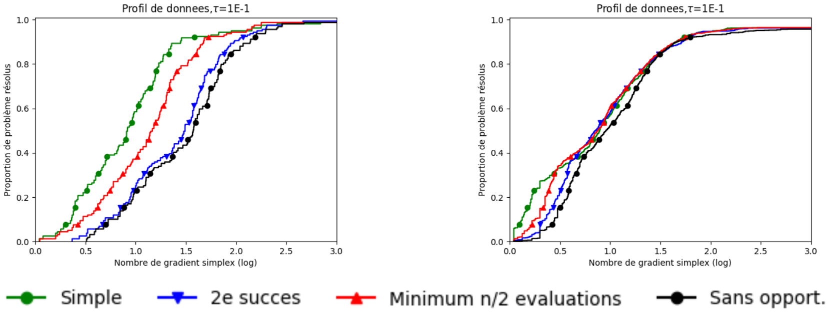

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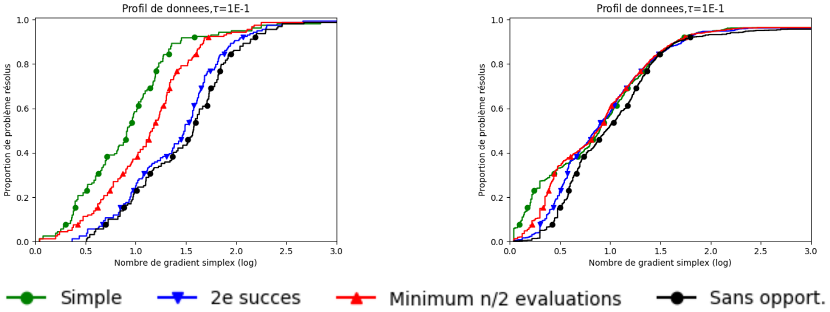

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3. Impact less important on MADS.

Ordering strategies comparison

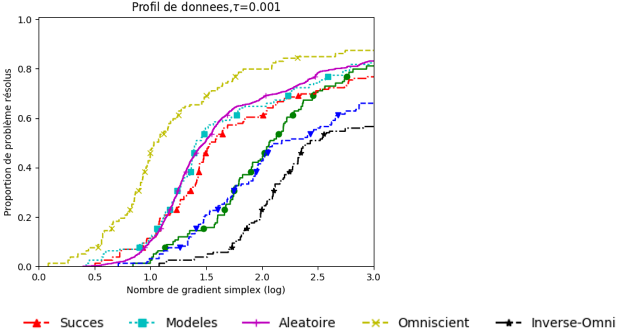

Figure: CS on Moré-Wild

Ordering strategies comparison

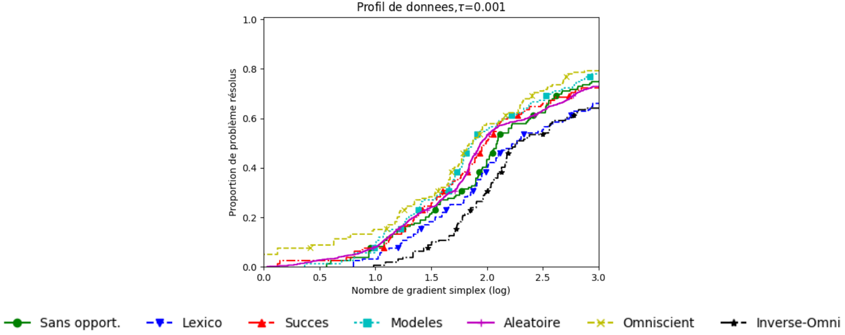

Figure: GPS on Moré-Wild

Ordering strategies comparison

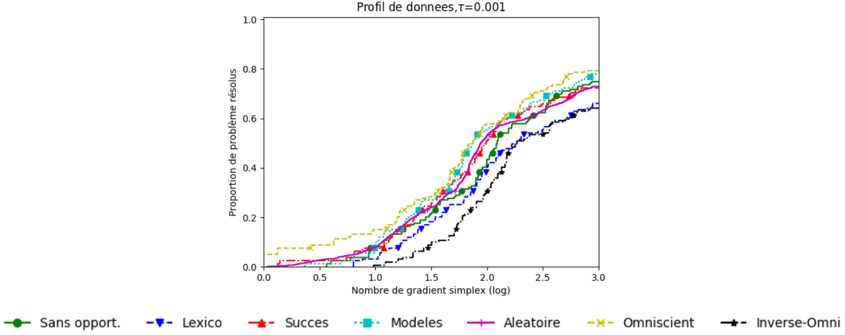

Figure: GPS on Moré-Wild

1. Omniscient strategy less dominant.

Ordering strategies comparison

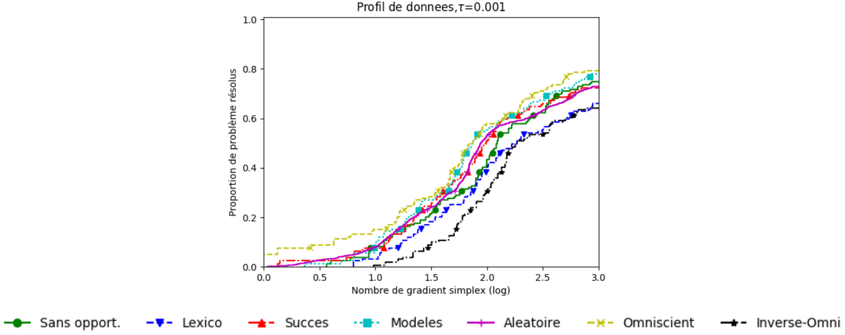

Figure: GPS on Moré-Wild

1. Omniscient strategy less dominant.
2. Somewhat similar hierarchy.

Ordering strategies comparison

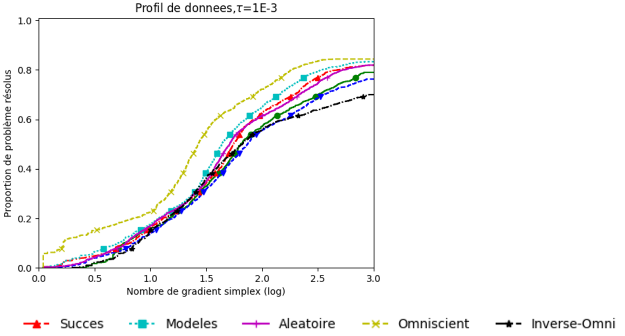

Figure: MADS on Moré-Wild

Ordering strategies comparison

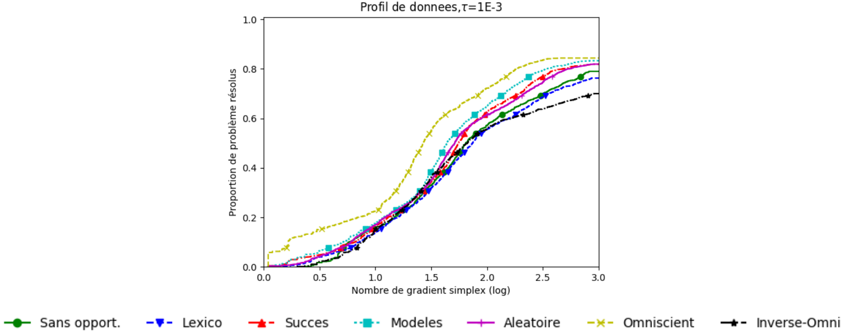

Figure: MADS on Moré-Wild

1. Impact less visible on MADS.

Ordering strategies comparison

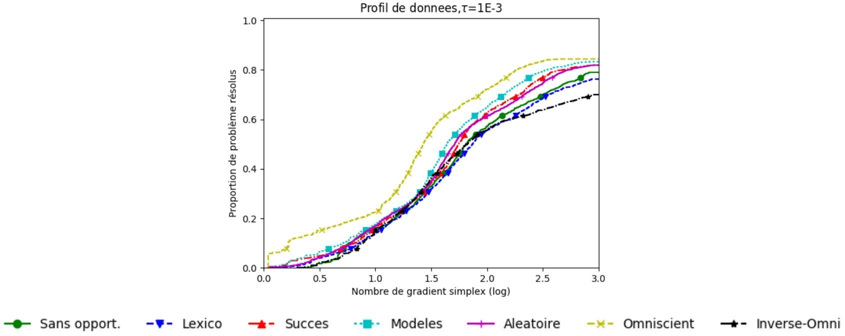

Figure: MADS on Moré-Wild

1. Impact less visible on MADS.
2. Different ranking of strategies on CS and MADS.

Ordering strategies comparison

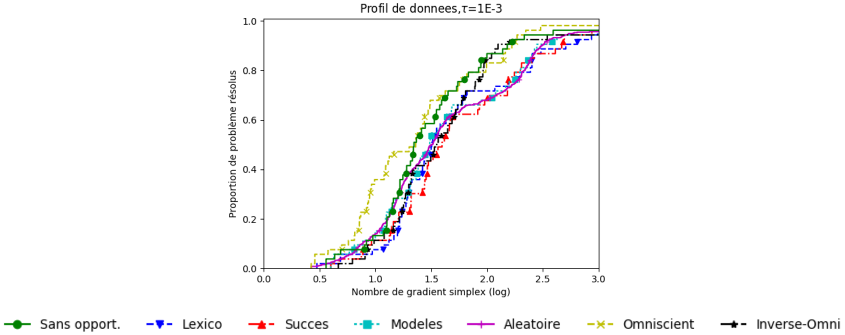

Figure: IMFIL on Moré-Wild

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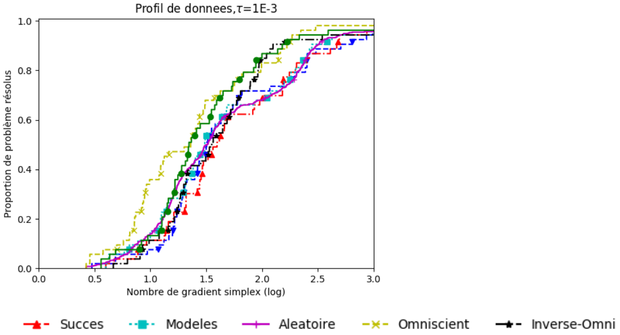

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1. Opportunism profitable with omniscient and reverse-omniscient only.

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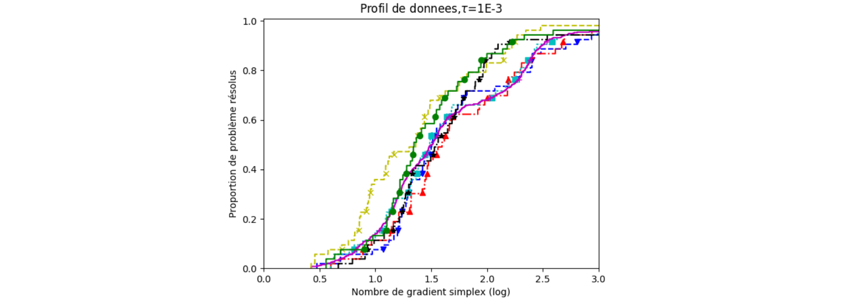


Figure: IMFIL on Moré-Wild

1. Opportunism profitable with omniscient and reverse-omniscient only.
2. Opportunism is harmful with the available realistic strategies.

Ordering strategies comparison

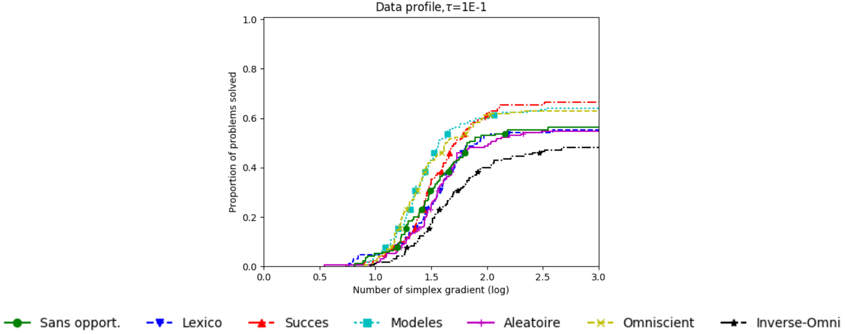
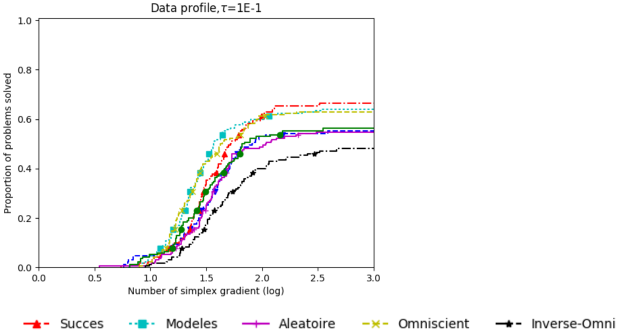


Figure: Constrained problems with MADS

Ordering strategies comparison



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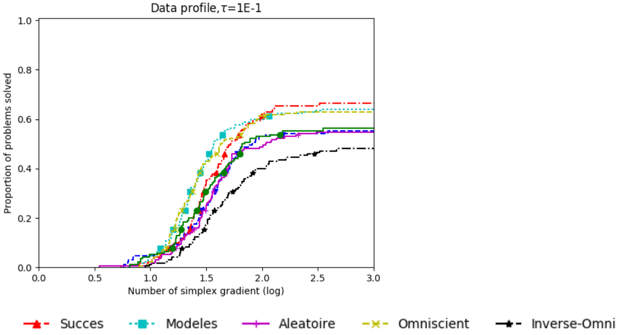

Figure: Constrained problems with MADS

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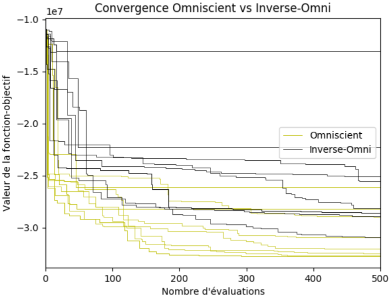
2. Surrogate ordering with progressive barrier might not be optimal.

Ordering strategies comparison



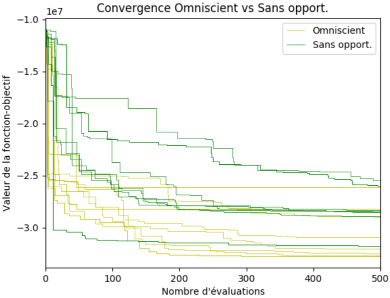


Figure: Comparing omniscient, reverse-omniscient and complete polling

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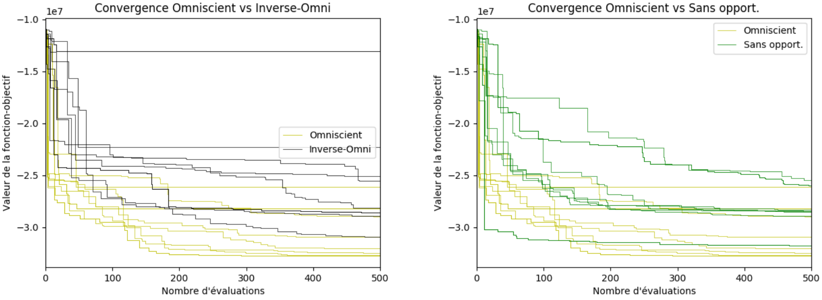

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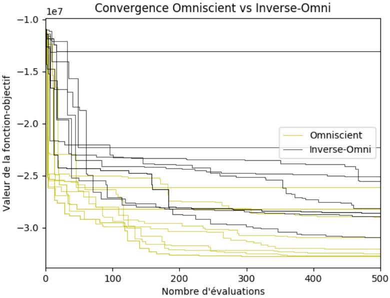

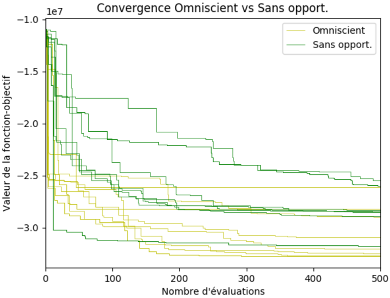

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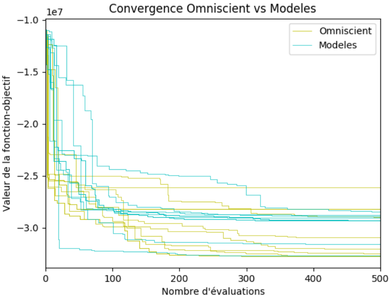

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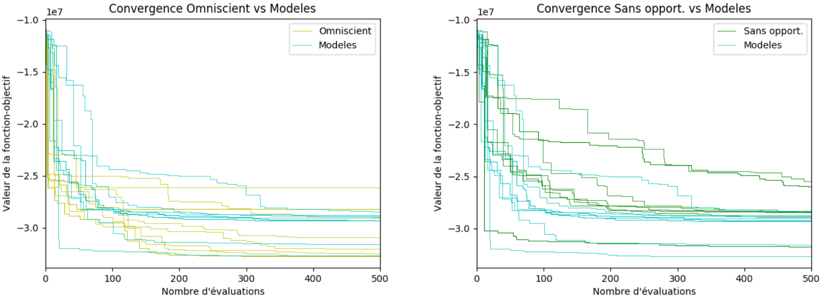
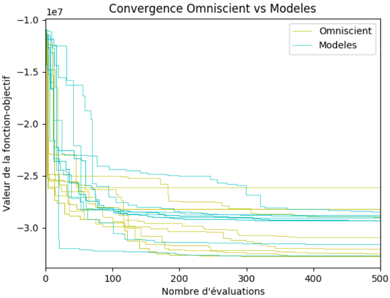


Figure: Comparing omniscient, model ordering and complete polling

1. Model ordering converges faster than complete polling.

Ordering strategies comparison



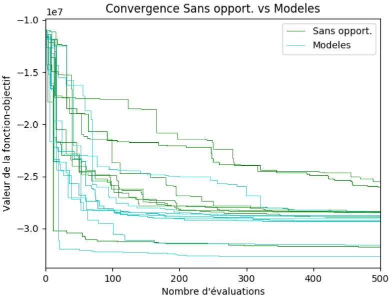


Figure: Comparing omniscient, model ordering and complete polling

1. Model ordering converges faster than complete polling.
2. Model ordering converges to a solution different from the one obtained from the omniscient ordering.

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2 Direct-search Methods

3 Opportunism and ordering

4 Numerical results

5 Conclusion

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References

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QUESTIONS?