

# A principled approach to automatically recommend optimization methods



Sofiane Tanji, François Glineur

UCLouvain

sofiane.tanji@uclouvain.be

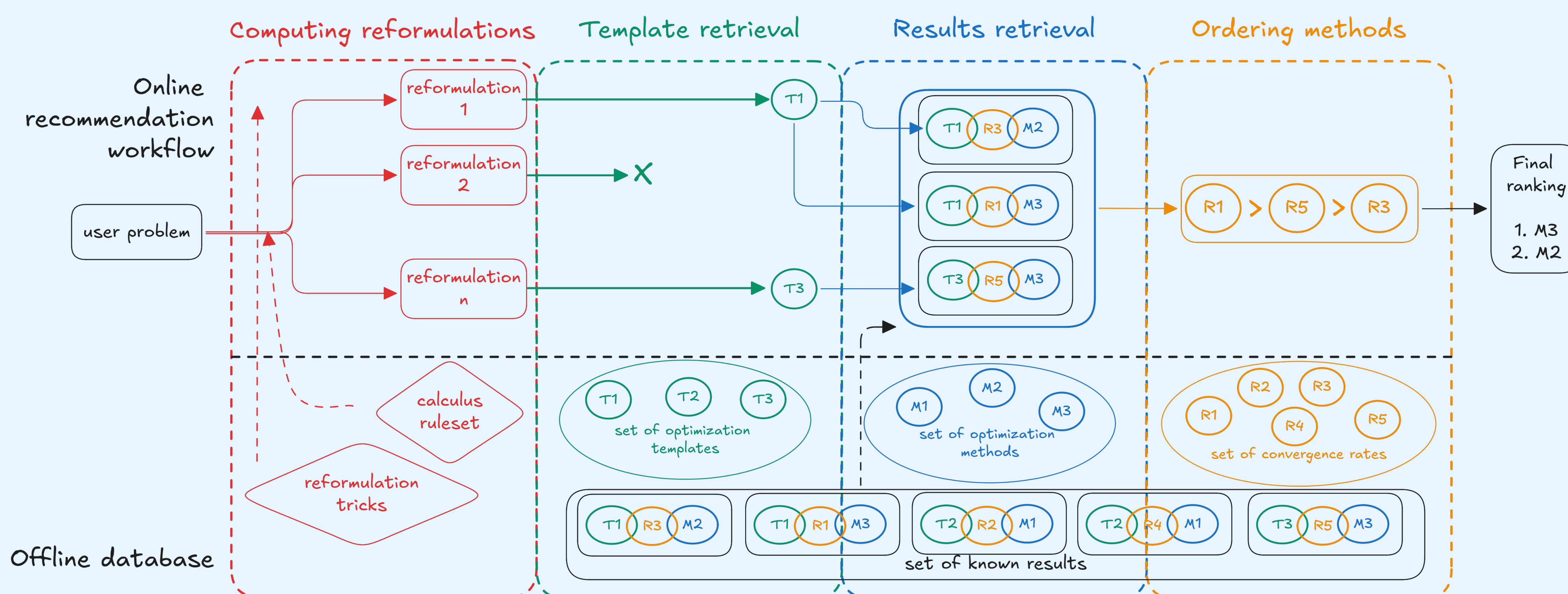


POSTER



SLIDES

## Our approach to recommend optimization methods



### Context

Find the best methods to efficiently solve the general problem

$$\min_{x \in \mathcal{X}} f(x) \quad (\text{OPT})$$

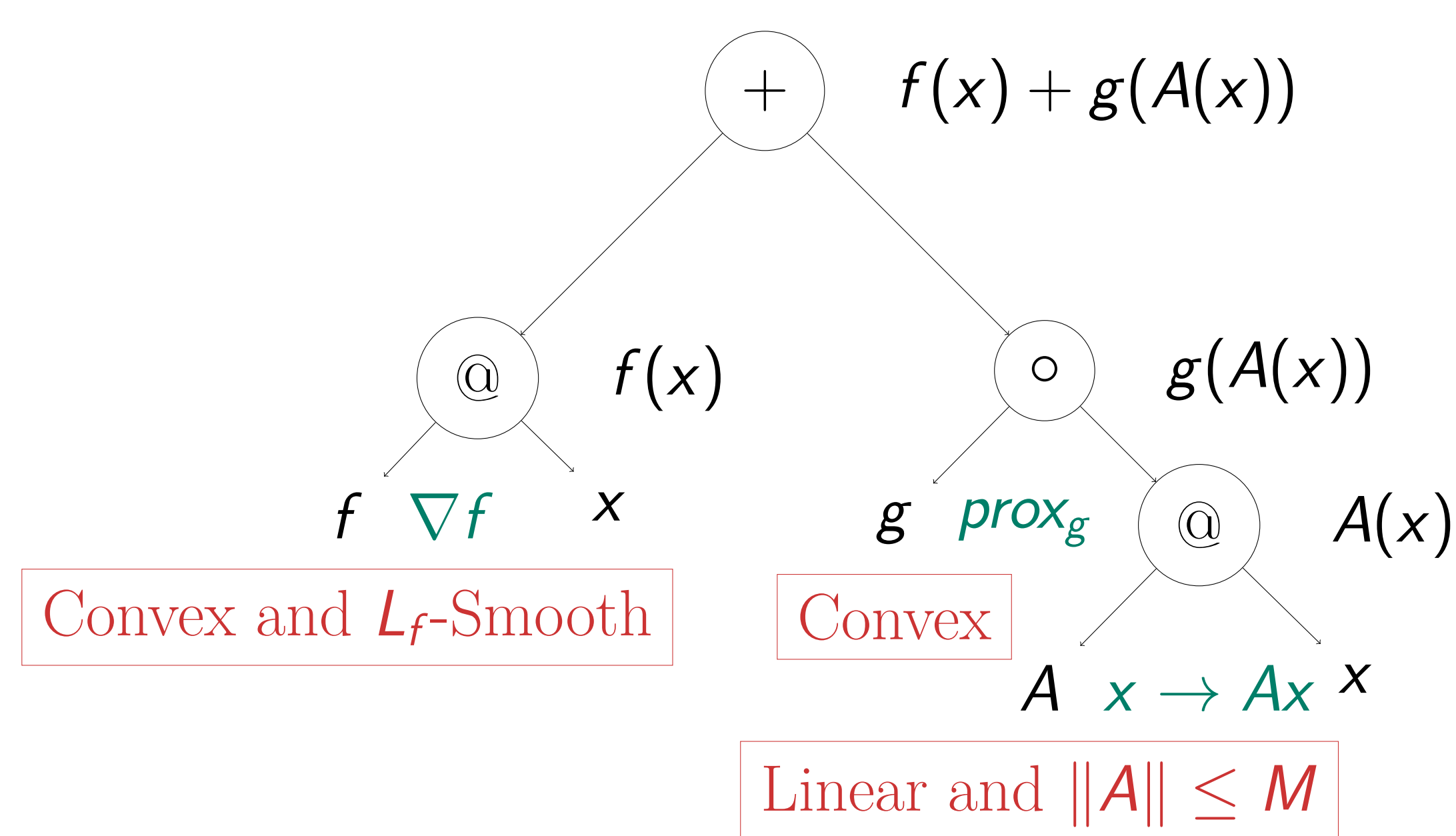
where  $f$  is composed of multiple subfunctions  $f_i$ , linked by common operators and involving multiple variables.

- ▶ Each  $f_i$  satisfy at least one assumption ( $L$ -Lipschitz gradient, convexity etc.)
- ▶ We access each  $f_i$  through black-box oracles (gradient, proximal operator etc.)

### Problem representation

$$\min_{x \in \mathbb{R}^n} f(x) + g(A(x)) \quad (1)$$

- ▶  $f : \mathbb{R}^n \rightarrow \mathbb{R}$  is convex,  $L_f$ -smooth. Access to  $\nabla f$ .
- ▶  $g : \mathbb{R}^m \rightarrow \mathbb{R}$  is convex. Access to  $\text{prox}_g$ .
- ▶  $A : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is a linear mapping with  $\|A\| \leq M$ . Access to  $x \rightarrow Ax$ .



### Code example

```
pb = Problem()
f = pb.declare_function("f", Rn, R)
g = pb.declare_function("g", Rn, R)
A = pb.declare_function("A", Rn, Rn)
x = pb.declare_variable("x", Rn)
f.add_property(Convex())
f.add_property(Smooth(0, 10.))
g.add_property(Convex())
A.add_property(Linear(0, 5.))
pb.declare_oracle(Derivative(f))
pb.declare_oracle(Proximal(g))
pb.declare_oracle(LinearMap(A))
pb.set_objective(f(x) + g(A(x)))
```

### Finding new reformulations

Ingredients used to compute new reformulations

1. **Elementary reformulation operations:** commutativity of operators, reparametrization, transfer of conditioning, losing structure etc.
2. **Calculus ruleset:** gradient/subgradient/prox/Fenchel calculus etc.

Compute (many) reformulations automatically by applying above tools to the original problem recursively

### Database of known results

**Claim:** All convergence theorems have the following form

**Theorem (informal): Worst-case convergence rate of Algorithm 1**

Suppose assumptions  $\mathcal{A} = \{A1, A2, A3\}$  hold. Consider initial conditions  $\mathcal{I}$ .

Then, Algorithm 1 with parameters  $\mathcal{P}$  applied to Problem (1) satisfies for all  $k \geq 1$

$$F(x_k) - F(x^*) \leq \varphi(k, \mathcal{A}, \mathcal{I}, \mathcal{P}) \quad (2)$$

meaning we have to encode 3 elements : **Template problem**, **Method parameters**, **Convergence rate**.

**Template problem:** a "common" optimization problem for which researchers provided convergence guarantees

**Method parameters:** any parameter appearing in the rate function, potentially based on an unknown quantity ( $L, \mu, \dots$ )

**Convergence rate:** a performance measure and a function upper bounding it as tight as possible.

### A ranking assistant

We rank optimization methods with a four-step approach:

1. **Automatic computation of reformulations**
2. **Template retrieval:** Match reformulations to known templates
3. **Results retrieval:** Query the database for all results associated to matched templates
4. **Ordering methods:** Compare retrieved convergence rates using heuristics
  - Drop asymptotically worse methods if iteration budget is high
  - Compare leading coefficients
  - Sample parameter values (if unknown) in provided range, allowing rate estimation