

Convex mixed-integer optimization with Frank-Wolfe methods

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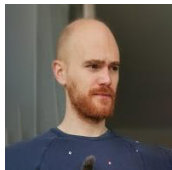


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Related Papers

- **Hendrych**, Troppens, Besançon, Pokutta: Convex Integer Optimization with Frank-Wolfe Methods, *Mathematical Programming Computation*, 2025
- **Hendrych**, Besançon, Pokutta: Solving the Optimal Experiment Design Problem with Mixed-Integer Convex Methods, *Proceedings of the Symposium on Experimental Algorithms*, 2024
- Xiao, **Hendrych**, Besançon, Pokutta: Boscia.jl: A Review and Tutorial, *arXiv preprint*, 2025



Mathieu Besançon

Inria, Université Grenoble



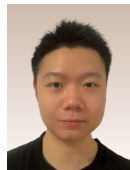
Sebastian Pokutta

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Outline

1. Mixed-Integer Convex Optimization

2. MICO with Frank-Wolfe

3. Examples

Portfolio Optimization

D-Optimal Experiment Design

Non-Convex Quadratic Problem

4. Outlook

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Mixed-Integer Convex Optimization

$$\begin{aligned} \min & f(\mathbf{x}) \\ \text{s.t.} & \mathbf{x} \in \mathcal{P} \\ & x_j \in \mathbb{Z} \quad \forall j \in J \end{aligned}$$

where

- f is a convex, L -smooth function.
- $\mathcal{P} \subset \mathbb{R}^n$ is polytope.
- $J \subset [n]$ is a set of indices.

Common Solution Approaches

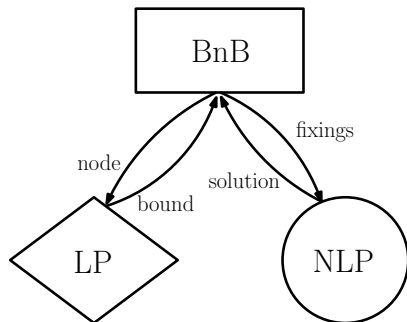
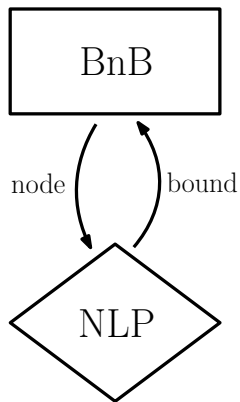


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Frank-Wolfe

Frank and Wolfe 1956; Levitin and Polyak 1966; Braun et al. 2022

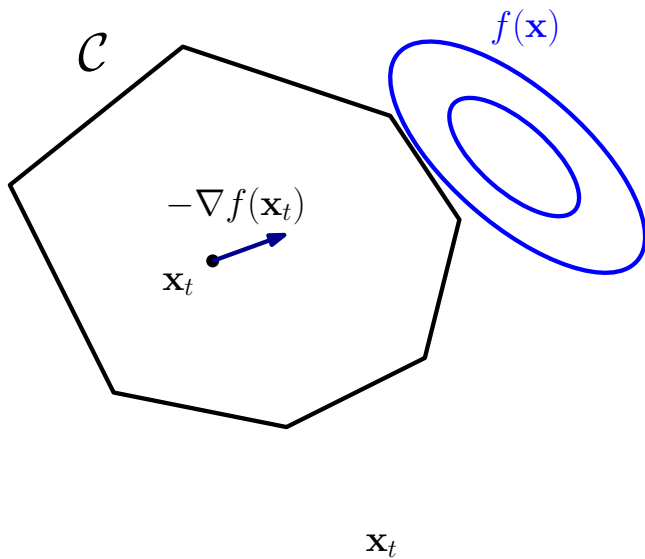
$$\begin{aligned} \min f(\mathbf{x}) \\ \text{s.t. } \mathbf{x} \in \mathcal{X} \end{aligned}$$

where

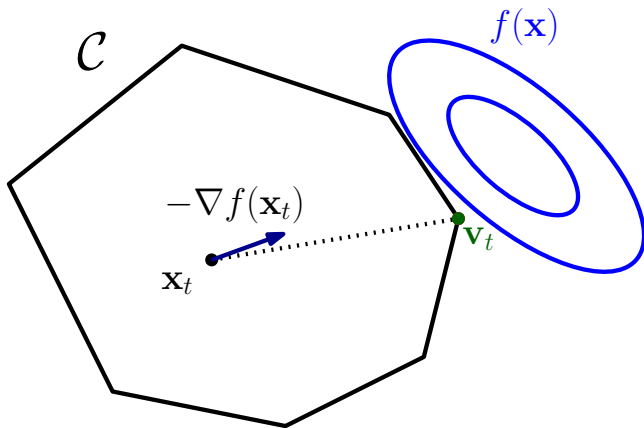
- f is a convex, L -smooth function.
- Oracle access to f and ∇f .
- $\mathcal{X} \subset \mathbb{R}^n$ is a compact convex set.
- \mathcal{X} admits an *efficient* Linear Minimization Oracle (LMO):

$$\arg \min_{\mathbf{v} \in \mathcal{X}} \langle \mathbf{d}, \mathbf{v} \rangle$$

Frank-Wolfe

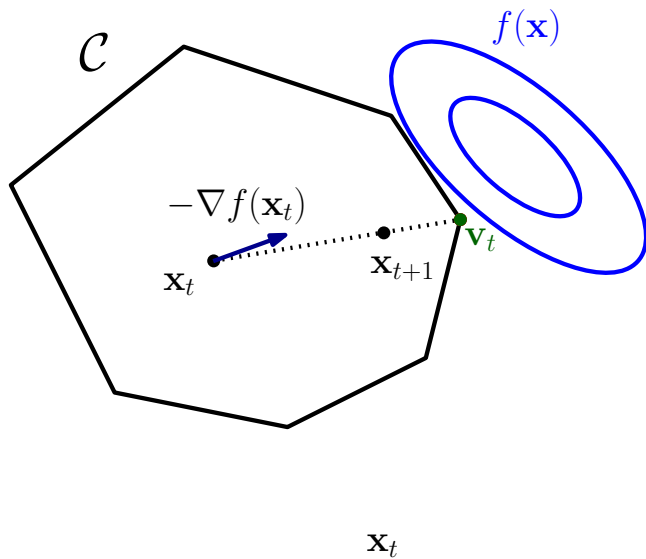


Frank-Wolfe

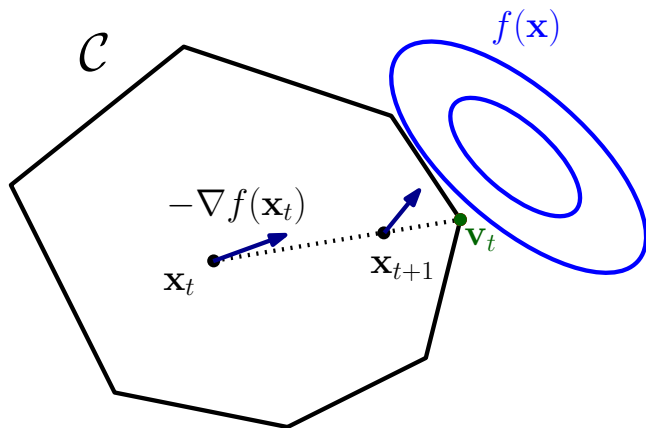


\mathbf{x}_t

Frank-Wolfe

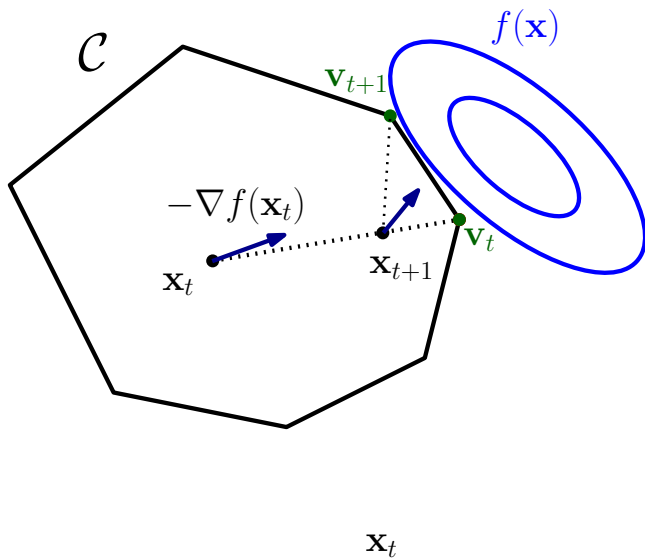


Frank-Wolfe



\mathbf{x}_t

Frank-Wolfe



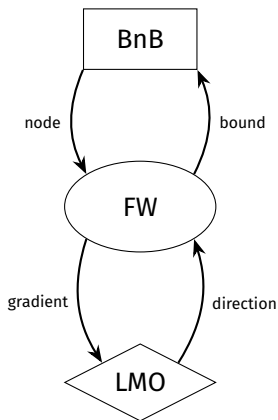
- \mathbf{x} is always feasible.
- iterate \mathbf{x}_t can be written as a convex combination of the vertices of \mathcal{X} , often stored as *active set*.
- Let \mathbf{x}^* an optimal solution. Then,

$$f(\mathbf{x}) - f(\mathbf{x}^*) \leq \langle \nabla f(\mathbf{x}), \mathbf{x} - \mathbf{x}^* \rangle \leq \max_{\mathbf{v} \in \mathcal{X}} \langle \nabla f(\mathbf{x}), \mathbf{x} - \mathbf{v} \rangle$$

is called the *Frank-Wolfe gap*.

BnB with Frank-Wolfe: Boscia

Hendrych et al. 2025



$$\begin{aligned} \min_{\mathbf{x}} \quad & f(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{x} \in \mathcal{P} \\ & x_j \in \mathbb{Z} \quad \forall j \in J \end{aligned}$$

$$\begin{aligned} \min_{\mathbf{x}} \quad & f(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{x} \in \text{conv}(\mathcal{P} \cap \mathbb{Z}_J) \end{aligned}$$

$$\begin{aligned} \min_{\mathbf{v}} \quad & \langle \nabla f(\mathbf{x}), \mathbf{v} \rangle \\ \text{s.t.} \quad & \mathbf{v} \in \mathcal{P} \cap \mathbb{Z}_J \end{aligned}$$

Branch-and-Bound with Frank-Wolfe: Boscia.jl

Key Features:

- Precision-adaptive Frank-Wolfe allows for a trade-off between accuracy and computational cost.
- Warm-starting nodes via splitting the active set of the parent node.
- Aggressive reuse of information: Lazification & shadow set techniques
- Built-in heuristic: Integer feasible solutions from root node.
- No closed form of the objective function required.
- No comprehensive description of the feasible region required.

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Portfolio Optimization I

Buchheim et al. 2018

$$\begin{aligned} \min \quad & \frac{1}{2} \mathbf{x}^T M \mathbf{x} - \mathbf{r}^T \mathbf{x} \\ \text{s.t.} \quad & \mathbf{a}^T \mathbf{x} \leq \mathbf{b} \\ & \mathbf{x} \geq \mathbf{0} \\ & x_j \in \mathbb{Z} \quad \forall i \in I \subseteq [n] \end{aligned}$$

where M is a psd matrix.

Portfolio Optimization II

Buchheim et al. 2018

```
model = Model(HiGHS.Optimizer)
set_silent(model)
@variable(model, x[1:n], Int)
@constraint(model, x[1:n] ≥ 0)
@constraint(model, dot(a, x) ≤ b)
@constraint(model, sum(x) ≥ 1.0)
lmo = FrankWolfe.MathOptLMO(model.moi_backend)

function f(x)
    return 1 / 2 * Ω * dot(x, M, x) - dot(r, x)
end
function grad!(storage, x)
    mul!(storage, M, x, Ω, 0)
    storage .-= r
    return storage
end

x, _, result = Boscia.solve(f, grad!, lmo)
```

D-Optimal Experiment Design I

Ponte et al. 2025; Ahipaşaoğlu 2021; Li et al. 2024; Pukelsheim 2006

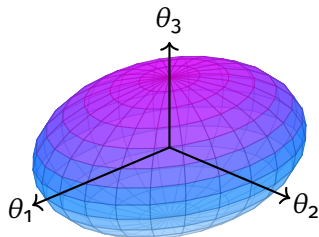
$$\min_{\mathbf{x}} -\log \det (A^{\top} \operatorname{diag}(\mathbf{x}) A)$$

$$\text{s.t. } \sum_{i=1}^m x_i = N$$

$$\mathbf{x} \geq \mathbf{0}$$

$$\mathbf{x} \in \mathbb{Z}^m.$$

(D)



D-Optimal Experiment Design II

Ponte et al. 2025; Ahipaşaoğlu 2021; Li et al. 2024; Pukelsheim 2006

```
simplex_lmo = Boscia.ProbabilitySimplexLMO(N)
lmo = Boscia.ManagedLMO(simplex_lmo, fill(0.0, m),
    fill(Float64(N), m), collect(1:m), m)

...

settings = Boscia.create_default_settings()
settings.branch_and_bound[:verbose] = true
settings.domain[:active_set] = copy(active_set)
settings.domain[:domain_oracle] = domain_oracle
settings.domain[:find_domain_point] = domain_point
settings.domain[:depth_domain] = 10
settings.frank_wolfe[:line_search] =
    FrankWolfe.Secant(domain_oracle=domain_oracle)

x, _, _ = Boscia.solve(f, grad!, lmo, settings=settings)
```

Non-Convex Quadratic Problem I

Mexi et al. 2025

$$\begin{aligned} \min \quad & \mathbf{x}^T \mathbf{Q} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \\ \text{s.t.} \quad & D \mathbf{x} \leq \mathbf{c} \\ & \mathbf{x} \in \{0, 1\}^n \end{aligned}$$

- Q is symmetric but not psd.
- Tackled them heuristically during the Land-Doig Competition.
- Frank-Wolfe only converges locally \rightarrow no valid lower bound.
- Wish: Plug-in user-provided lower bound.

Non-Convex Quadratic Problem II

Mexi et al. 2025

```
model = Model(HiGHS.Optimizer)
@variable(model, x[1:n], Bin)
@constraint(model, x[1:n] ≥ 0)
@constraint(model, D*x ≤ c)
lmo = FrankWolfe.MathOptLMO(model.moi_backend)

function f(x)
    return 1 / 2 * dot(x, Q, x) + dot(q, x)
end
function grad!(storage, x)
    mul!(storage, Q, x, 1, 0)
    storage .-= q
    return storage
end

settings = Boscia.create_default_settings(mode=Boscia.HEURISTIC_
    MODE)
settings.branch_and_bound[:verbose] = true
x, _, result = Boscia.solve(f, grad!, lmo, settings=settings)
```

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Outlook

Practicality and UI

- Connect to MathOptInterface (MOI) and JuMP.
- Web service.
- Precompiled and executable version.

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Practicality and UI

- Connect to MathOptInterface (MOI) and JuMP.
- Web service.
- Precompiled and executable version.

Capabilities

- Preprocessing and propagation.
- Convergence with extended smoothness definitions.
- Non-convex objective function.

Thank you for your attention!

Convex mixed-integer optimization
with Frank–Wolfe methods



Boscia.jl



References I

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