



# Bundlemethods

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# Problem

$$(P) \quad \min c^T x, \quad c, x \in \mathbb{R}^n$$

*s.t.*

$$(i) \quad Ax = a, \quad A \in \mathbb{R}^{m' \times n}, \quad \text{“difficult” constraints}$$

$$(ii) \quad Bx = b, \quad B \in \mathbb{R}^{m'' \times n}, \quad \text{“easy” constraints}$$

$$(iii) \quad x \geq 0.$$

Questions:

- find a lower bound for (P),
- calculate a solution  $x^*$  of (P).

# Lagrangian Relaxation

Lagrangian relaxation of (P):

$$\begin{aligned}
 \text{(L)} \quad & \max_{\lambda \in \mathbb{R}^{m'}} \quad \min c^T x + \lambda^T (a - Ax) \\
 & \text{s.t.} \\
 \text{(ii)} \quad & Bx = b, \\
 \text{(iii)} \quad & x \geq 0.
 \end{aligned}$$

Lagrangian function:

$$f(\lambda) := \min_{Bx=b, x \geq 0} \overbrace{\lambda^T a + (c^T - \lambda^T A)x}^{L(x;\lambda) :=}$$

Lagrangian problem:  $\max_{\lambda} f(\lambda)$ .

# Conventional Subgradient Methods

$$\text{Solve (L): } \max_{\lambda} \min_{Bx=b, x \geq 0} L(x; \lambda)$$

1. Initialization:

Let  $i \leftarrow 0$ , select Lagrangean multipliers  $\lambda_0$  and a solution  $x_0$  of  $\min_{Bx=b, x \geq 0} L(x; \lambda_0)$ .

2.  $v_i \leftarrow a - Ax_i$

3. Update of the Lagrangean multipliers:

$$\lambda_{i+1} \leftarrow \lambda_i + s_i v_i / \|v_i\|, \quad s_i \in \mathbb{R}_+.$$

4. Solve  $\min_{Bx=b, x \geq 0} L(x, \lambda_{i+1})$ , let  $x_{i+1}$  a solution.

5.  $i \leftarrow i + 1$ .

6. go to step 2.

# Properties of Subgradient Methods

$$(P) \quad \min c^T x, \quad \text{s. t. } Ax = a, \quad Bx = b, x \geq 0$$

$$(L) \quad \max_{\lambda} f(\lambda).$$

$$f(\lambda) := \min_{Bx=b, x \geq 0} L(x; \lambda), \quad L(x; \lambda) := c^T x - \lambda^T (a - Ax)$$

- $(\lambda_i)_{i=0,1,\dots}$  converges theoretically to an optimal solution of (L), if  $(s_i)_{i \in \mathbb{R}}$  is selected appropriately (Polyak 1969, Shor 1985):

$$\lim_{i \rightarrow \infty} s_i = 0, \quad \sum_{i=0}^{\infty} s_i = \infty, \quad \left( \text{e. g. } s_i = \frac{1}{i} \right)$$

- Every value of  $f(\lambda)$  is a lower bound for (P).
- Numerically not stable (no convergence in practice).
- No solution for the primal problem, i. e.,  $Ax_i = a$  does not hold in general.

# Bundlemethod: Idea

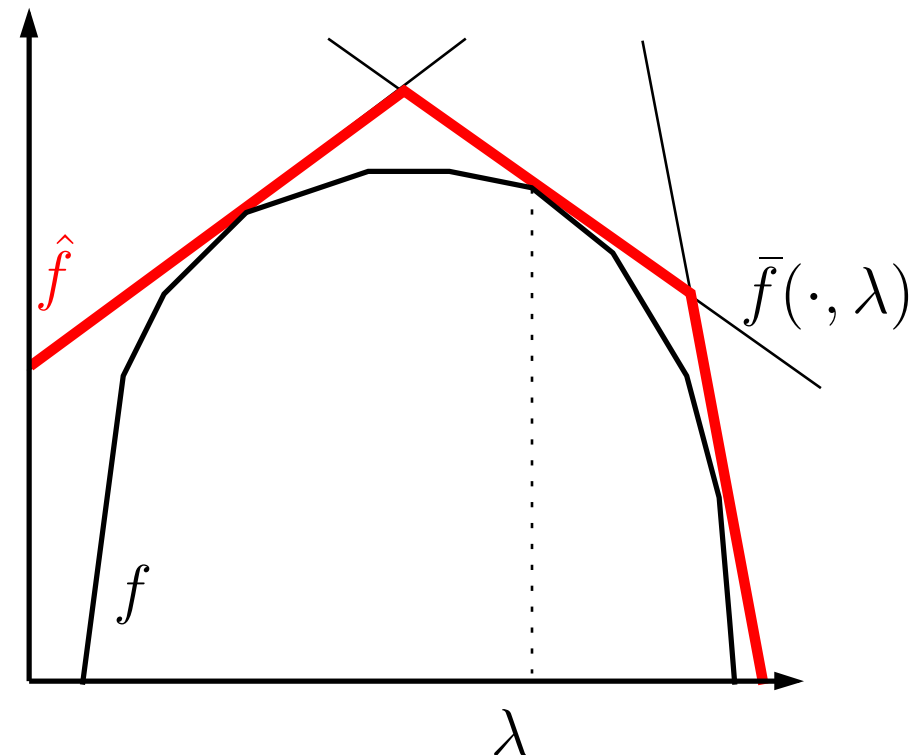
Helmberg, Kiewiel 2002

Idea: Do not use a single subgradient  $a - Ax_i$  at each iteration, but a bundle of subgradients.

$$\bar{f}(\mu; \lambda) := f(\mu) + g(\mu)^T (\lambda - \mu)$$

$$\hat{f}_J(\lambda) := \min_{\mu \in J} \bar{f}(\mu; \lambda)$$

$$\tilde{f}_J(\hat{\lambda}; \lambda) := \hat{f}_J(\lambda) - \|\lambda - \hat{\lambda}\|^2$$



# Bundlemethod: Algorithm

$$\text{Solve (L): } \max_{\lambda} \min_{Bx=b, x \geq 0} L(x; \lambda)$$

## 1. Initialization:

Let  $i \leftarrow 0$ , select Lagrangean multipliers  $\lambda_0$  and a solution  $x_0$  of  $\min_{Bx=b, x \geq 0} L(x; \lambda_0)$ . Let  $\hat{\lambda}_0 \leftarrow \lambda_0$ .

2. Solve  $\lambda = \operatorname{argmax}_{\lambda} \tilde{f}_J(\hat{\lambda}_i; \lambda)$ .

3. Update Lagrangean multipliers:  $\lambda_{i+1} \leftarrow \lambda$ .

4. Update Stability Center: if  $f(\lambda)$  good enough, let  $\hat{\lambda}_{i+1} \leftarrow \lambda$ , otherwise  $\hat{\lambda}_{i+1} \leftarrow \hat{\lambda}_i$ .

5.  $i \leftarrow i + 1$ .

6. go to step 2.

# Solving the Quadratic Problem

Problem:  $\max_{\lambda} \tilde{f}_J(\hat{\lambda}; \lambda)$ .

Remember:

$$\begin{aligned} \tilde{f}_J(\hat{\lambda}; \lambda) &:= \hat{f}_J(\lambda) - \|\lambda - \hat{\lambda}\|^2 \\ &= \min_{\mu \in J} \left[ \bar{f}(\mu; \lambda) - \|\lambda - \hat{\lambda}\|^2 \right]. \end{aligned}$$

Then holds

$$\begin{aligned} \max_{\lambda} \tilde{f}_J(\hat{\lambda}; \lambda) &\iff \max u - \|\lambda - \hat{\lambda}\|^2, \\ &\text{s.t. } u - \bar{f}(\mu; \lambda) \leq 0, \quad \forall \mu \in J. \end{aligned}$$

and this is equivalent to

$$\begin{aligned} \max \sum_{\mu \in J} \alpha_{\mu} \bar{f}(\mu; \lambda) - \left\| \sum_{\mu \in J} \alpha_{\mu} g(\mu) \right\|^2, \\ \text{s.t. } \sum_{\mu \in J} \alpha_{\mu} = 1, \\ \alpha_{\mu} \geq 0, \quad \forall \mu \in J. \end{aligned}$$



# Properties of the Bundlemethod

- $(f(\hat{\lambda}_i))_{i=0,1,\dots}$  converges to the optimal value of (P).
- One can find a series  $(x_i)_{i=0,1,\dots}$  converging to an optimal solution  $x^*$  of (P).
- works in applications:
  - Set-partitioning with additional knapsack constraints,
  - multi-commodity-flow,
  - shortest-path-problems with additional linear constraints (RCSP),
  - integrated duty and vehicle scheduling problem.

# Implementation

Spectral Bundle Method of Ch. Helmberg for semidefinite programming available at

<http://www-user.tu-chemnitz.de/~helmberg/>

- Manages bundle,
- solves quadratic problem,
- approximates primal solution.

C and C++ Interfaces for SBMETHOD to solve linear programming are also available.

# Interface

Solve problem of type

- (P)  $\min c^T x, \quad c, x \in \mathbb{R}^n$
- (i)  $\text{s.t. } Ax = a, \quad A \in \mathbb{R}^{m' \times n}, \quad \text{“difficult” constraints}$
- (ii)  $Bx = b, \quad B \in \mathbb{R}^{m'' \times n}, \quad \text{“easy” constraints}$
- (iii)  $x \geq 0.$

User has to implement a procedure which solves

$$\min_{Bx=b, x \geq 0} (c - \lambda^T A)x$$

for a given  $\lambda$  and returns a minimizer  $x^0$ , a subgradient  $a - Ax^0$  and the objective value  $(c - \lambda^T A)x^0$ .

# Extensions

- Special handling of separable functions,
- inequality constraints,
- dynamic addition of constraints,
- $\epsilon$ -subgradients.

# Running Times

Set partitioning problem with 3,570 rows and 838,500 columns.

