TUTORIAL ON STOCHASTIC PROGRAMMING & BENDERS DECOMPOSITION

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LINEAR PROGRAMMING [1]

■ The primal form:

$$nin \sum c_i x_i \tag{1.1}$$

s.t.
$$\sum_{i} a_{j,i} x_i = b_j \quad \forall \ j = 1, \dots, m;$$
 (1.2)

$$x_i \ge 0 \quad \forall \ i = 1 \dots, n. \tag{1.3}$$

GRAPHIC REPRESENTATION

■ Polyhedron;

Prerequisite

■ In two dimensions, i.e., $\mathbf{x} = (x_1, x_2)^T$:

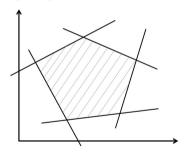


FIGURE: A polyhedron constructed using linear equations.

DUAL

Prerequisite

- "Rotate the primal 90° to the left":
- The primal form:

$$\min \quad \sum c_i x_i \tag{1.4}$$

s.t.
$$\sum_{i} a_{j,i} x_i = b_j \quad \forall \ j = 1, \dots, m;$$
 (1.5)

$$x_i \ge 0 \quad \forall \ i = 1 \dots, n. \tag{1.6}$$

■ The dual form:

$$\max \sum_{i} b_{j} y_{j} \tag{1.7}$$

s.t.
$$\sum_{j} a_{j,i} y_j \leq c_i \quad \forall \ i=1,\ldots,n;$$

$$y_j$$
 unrestricted $\forall j = 1..., m.$ (1.9)

(1.8)

FARKAS' LEMMA

- "Either the program is feasible, or infeasible";
- Exactly one of the following two holds:
 - There exists $x \succeq 0$, such that $\sum_i a_{j,i} x_i = b_j, \forall j = 1, \ldots, m$;
 - There exists y, such that $\sum_i a_{j,i} y_j \ge 0, \forall i = 1, ..., n$ and $\sum_i b_i y_i < 0$.

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EXAMPLE: PRODUCTION

- Produce two products: *A* and *B*;
- Revenue:

- A: 40:
 - B: 50;
- Required material:
 - \blacksquare A: 1 α and 3 β ;
 - \blacksquare B: 1 α , 4 β and 1 γ ;
- Material cost:
 - **α**: 10;
 - **■** *β*: 1;
 - γ: 1.

EXAMPLE: PRODUCTION (CONT.)

Demand:

- A: 20;
- *B*: 60:
- Salvage cost:
 - α: 0;
 - **β**: 0.1;
 - **■** *γ*: 0.1.
- How do we produce A and B, and how much material to purchase?

EXAMPLE: LP

- Variables:
 - x: material purchase;
 - y: production;
 - z: remaining material.
- LP:

$$\min \quad 10x_{\alpha} + 1x_{\beta} + 1x_{\gamma} - 40y_{A} - 50y_{B} - 0z_{\alpha} - 0.1z_{\beta} - 0.1z_{\gamma} \tag{1.10}$$

s.t.
$$z_{\alpha} = x_{\alpha} - 1 \cdot y_{\mathcal{A}} - 1 \cdot y_{\mathcal{B}};$$
 (1.11)

$$z_{\beta} = x_{\beta} - 3 \cdot y_{A} - 4 \cdot y_{B}; \tag{1.12}$$

$$z_{\gamma} = x_{\gamma} - 0 \cdot y_A - 1 \cdot y_B; \tag{1.13}$$

$$x \ge 0, z \ge 0; \tag{1.14}$$

$$0 \le y_A \le 20, 0 \le y_B \le 60. \tag{1.15}$$

EXAMPLE: LP (CONT.)

Concisely:

- \blacksquare q_i : revenue of i;
- \mathbf{d}_i : demand of i:
- \blacksquare $m_{i,i}$: product i using material j;
- c_i : cost of j;
- \bullet s_i : salvage cost of i:
- LP:

$$\min \sum_{i=\alpha}^{\gamma} c_j x_j - \sum_{i=A}^{B} q_i y_i - \sum_{i=\alpha}^{\gamma} s_j z_j$$
 (1.16)

s.t.
$$z_j = x_j - \sum_{i=1}^{B} m_{i,j} y_i \quad \forall \ j = \alpha, \beta, \gamma;$$
 (1.17)

$$x \ge 0, z \ge 0, 0 \le y_i \le d_i, \forall i. \tag{1.18}$$

Uncertain Future

- E.g., stochastic demand;
- Scenarios, k = 1, 2, 3:
 - With pr. $p_1 = 0.3$, $d_A = 10$, $d_B = 30$;
 - With pr. $p_2 = 0.5$, $d_A = 20$, $d_B = 60$;
 - With pr. $p_3 = 0.2$, $d_A = 40$, $d_B = 80$;
- How should we process this information?

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- How should we process this information?

- Wait & see (WS):
 - Perfect information, knows the future:
 - Have three purchase & production plans according to each of the scenario;
- Here & now:
- Expected value (EV):
- \blacksquare WS \leq RP \leq EV.

- Wait & see (WS):
 - Perfect information, knows the future:
 - Have three purchase & production plans according to each of the scenario:
- Here & now:
 - Know the future up to a distribution;
 - Have only one purchase plans, but three production plans according to each of the scenario:
 - Recourse policy (RP);
- Expected value (EV):
- WS < RP < EV.

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 - Know the future up to a distribution;
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- WS < RP < EV.

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 - Know the future up to a distribution;
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- WS \leq RP \leq EV.

FORMULATION: EXTENSIVE FORM

Adopting RP:

$$\min \sum_{i=\alpha}^{\gamma} c_j x_j + \sum_{k=1}^{3} p_k \cdot \left(-\sum_{i=A}^{B} q_i y_i^k - \sum_{i=\alpha}^{\gamma} s_j z_j^k \right)$$
 (2.1)

s.t.
$$z_j^k = x_j - \sum_{i=1}^{B} m_{i,j} y_i^k \quad \forall \ j = \alpha, \beta, \gamma, k = 1, 2, 3;$$
 (2.2)

$$x_i \ge 0 \quad \forall \ j = \alpha, \beta, \gamma;$$
 (2.3)

$$0 < y_i^k < d_i \quad \forall \ i = A, B, k = 1, 2, 3;$$
 (2.4)

$$z_j \ge 0 \quad \forall \ j = \alpha, \beta, \gamma, k = 1, 2, 3. \tag{2.5}$$

GENERIC FORM [2]

- Variable in the present: x;
- Variable in the future: **y**;
- The generic extensive form:

min
$$oldsymbol{c}^T oldsymbol{x} + \mathbb{E}_{\xi} ig[\min oldsymbol{q}^T(\xi) oldsymbol{y}(\xi) ig]$$

s.t.
$$Ax = b$$
;

$$T(\xi)\mathbf{x} + W\mathbf{y}(\xi) = \mathbf{h}(\xi); \tag{2.8}$$

$$\mathbf{x} \succeq \mathbf{0}, \mathbf{y}(\xi) \succeq \mathbf{0}. \tag{2.9}$$

(2.6)

(2.7)

PROBLEM OF INTEREST [3]

■ Two variables, \mathbf{x} and \mathbf{v} :

$$\max \quad \boldsymbol{c}^T \boldsymbol{x} + f(\boldsymbol{y})$$

s.t.
$$A\mathbf{x} + F(\mathbf{y}) \leq \mathbf{b}$$
;

$$\mathbf{x} \in R^p, \mathbf{y} \in S^q$$
.

(3.1)

■ Equivalent form:

$$\max x_0$$

s.t.
$$x_0 - c^T x - f(y) < 0$$
;

$$Ax + F(y) \leq b$$
;

$$x \in R^p, v \in S^q$$

PROBLEM OF INTEREST [3]

 \blacksquare Two variables, x and y;

$$\max \quad \boldsymbol{c}^{\mathsf{T}}\boldsymbol{x} + f(\boldsymbol{y}) \tag{3.1}$$

s.t.
$$A\mathbf{x} + F(\mathbf{y}) \leq \mathbf{b}$$
;

$$\mathbf{x} \in R^p, \mathbf{y} \in S^q. \tag{3.3}$$

s.t.
$$x_0 - c^T x - f(y) \le 0$$
;

$$A\mathbf{x} + F(\mathbf{y}) \prec \mathbf{b}$$
:

$$\mathbf{x} \in R^p, \mathbf{y} \in S^q. \tag{3.7}$$

(3.2)

(3.4)

(3.5)

(3.6)

USING FARKAS' LEMMA

- Consider fixed \bar{y} and arbitrary \bar{x}_0 ;
- Feasible region for *x* becomes

$$\begin{cases}
-\mathbf{c}^T \mathbf{x} \le -\bar{\mathbf{x}}_0 + f(\bar{\mathbf{y}}); \\
A\mathbf{x} \le \mathbf{b} - F(\bar{\mathbf{y}})
\end{cases} (3.8)$$

- Lagrangian multiplier (dual variable) μ_0 , μ ;
- Region (3.8) is feasible **if and only if**

$$\mu_0 \bar{\mathbf{x}}_0 - \mu_0 f(\bar{\mathbf{y}}) + \boldsymbol{\mu}^T F(\bar{\mathbf{y}}) \le \boldsymbol{\mu}^T \mathbf{b}, \tag{3.9}$$

$$\forall (\mu_0, \mu) \in \mathcal{C} := \{ (\mu_0, \mu) : A^T \mu - \mu_0 \mathbf{c} \succeq \mathbf{0}, \mu \succeq \mathbf{0}, \mu_0 \ge 0 \}.$$
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 (3.10)

Benders Decomposition

Using Farkas' Lemma

- Consider fixed $\bar{\mathbf{y}}$ and arbitrary \bar{x}_0 ;
- Feasible region for x becomes

$$\begin{cases}
-\mathbf{c}^{\mathsf{T}}\mathbf{x} \leq -\bar{\mathbf{x}}_0 + f(\bar{\mathbf{y}}); \\
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$$\forall \ (\mu_0, \mu) \in C := \{ (\mu_0, \mu) : A^T \mu - \mu_0 c \succeq 0, \mu \succeq 0, \mu_0 \ge 0 \}.$$
 (3.10)

GRAPHIC ILLUSTRATION

Define

$$G := \bigcap_{(\boldsymbol{\mu}_0, \boldsymbol{\mu}) \in C} \left\{ (\boldsymbol{x}_0, \boldsymbol{y}) : \mu_0 \boldsymbol{x}_0 - \mu_0 f(\boldsymbol{y}) + \boldsymbol{\mu}^T F(\boldsymbol{y}) \le \boldsymbol{\mu}^T \boldsymbol{b} \right\}; \tag{3.11}$$

■ Finite halflines h = 1, 2, ..., H.

$$G := \bigcup_{h=1,2,...,H} \left\{ (x_0, \mathbf{y}) : \mu_0^h x_0 - \mu_0^h f(\mathbf{y}) + \mu^{h^T} F(\mathbf{y}) \le \mu^{h^T} \mathbf{b} \right\}.$$
(3.12)

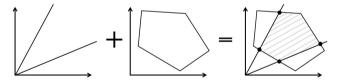


FIGURE: Intersecting a polyhedron with a cone.

GRAPHIC ILLUSTRATION

Define

$$G := \bigcap_{(\mathbf{x}_0, \mathbf{y}) \in \mathcal{G}} \left\{ (\mathbf{x}_0, \mathbf{y}) : \mu_0 \mathbf{x}_0 - \mu_0 f(\mathbf{y}) + \boldsymbol{\mu}^T F(\mathbf{y}) \le \boldsymbol{\mu}^T \boldsymbol{b} \right\}; \tag{3.11}$$

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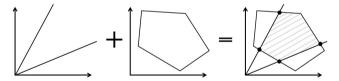


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Equivalence to The Original Problem

■ The problem (♦)

s.t.
$$x_0 \in \{x_0 : (x_0, \mathbf{v}) \in G\}$$

is equivalent to the problem (\heartsuit)

s.t.
$$x_0 - c^T x - f(y) \le 0$$
;

$$A\mathbf{x} + F(\mathbf{v}) \prec \mathbf{b}$$
:

$$x \in R^p, v \in S^q$$
.

OPTIMAL SOLUTIONS

- Let (x_0^*, \mathbf{y}^*) be an optimal solution to (\diamondsuit) ;
- There must exist x^* , such that x^* is an optimal solution to (\heartsuit) ;
- We know

$$\begin{cases} x_0^* = c^T x^* + f(y^*); \\ x_0^* \ge c^T x + f(y^*) & \forall x. \end{cases}$$
 (3.19)

 \blacksquare To find x^* , solve

$$\max \quad \boldsymbol{c}^{\mathsf{T}}\boldsymbol{x} \tag{3.20}$$

s.t.
$$A\mathbf{x} \leq \mathbf{b} - F(\mathbf{y}^*);$$
 (3.21)

$$x \succeq \mathbf{0}. \tag{3.22}$$

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DECOMPOSITION

■ Master problem:

s.t.
$$x_0 \in \{x_0 : (x_0, \mathbf{y}) \in G\}.$$

■ Subproblem:

$$\max c^T x$$

s.t.
$$A\mathbf{x} \leq \mathbf{b} - F(\mathbf{y}^*)$$
;

$$x \succ 0$$
.

STOCHASTIC: TWO-STAGE

Master problem:

Benders Decomposition

$$\min \quad \boldsymbol{c}^T \boldsymbol{x} + \mathcal{Q}(\boldsymbol{x})$$

(3.28)

s.t.
$$Ax = b$$
;

$$x \succ 0, \tag{3.30}$$

where
$$\mathcal{Q}(\mathbf{x}) := \mathbb{E}_{\xi}[Q(\mathbf{x}, \xi)];$$

■ Subproblem:

$$Q(\boldsymbol{x},\xi) := \min \quad \boldsymbol{q}^T(\xi)\boldsymbol{y}(\xi)$$

$$oldsymbol{q}^T(\xi)oldsymbol{y}(\xi)$$

s.t.
$$T(\xi)\mathbf{x} + W\mathbf{y}(\xi) = \mathbf{h}(\xi)$$
;

$$\mathbf{v}(\xi) \succeq \mathbf{0}$$
.

RECALL: THE PRODUCTION PROBLEM

■ Extensive form:

$$\min \sum_{i=\alpha}^{\gamma} c_j x_j + \sum_{k=1}^{3} p_k \cdot \left(-\sum_{i=A}^{B} q_i y_i^k - \sum_{i=\alpha}^{\gamma} s_j z_j^k \right)$$
(3.34)

s.t.
$$z_j^k = x_j - \sum_{i=1}^B m_{i,j} y_i^k \quad \forall \ j = \alpha, \beta, \gamma, k = 1, 2, 3;$$
 (3.35)

$$x_i \ge 0 \quad \forall \ j = \alpha, \beta, \gamma;$$
 (3.36)

$$0 \le y_i^k \le d_i^k \quad \forall \ i = A, B, k = 1, 2, 3;$$
 (3.37)

$$z_j \ge 0 \quad \forall \ j = \alpha, \beta, \gamma, k = 1, 2, 3. \tag{3.38}$$

REFORMULATE THE PRODUCTION PROBLEM

■ Master problem:

$$\min \sum_{j=\alpha}^{\gamma} c_j x_j + \sum_{k=1}^{3} p_k \cdot Q(x,k)$$
(3.39)

s.t.
$$x_i \ge 0 \quad \forall \ j = \alpha, \beta, \gamma;$$
 (3.40)

■ Subproblems, $\forall k = 1, 2, 3$:

$$Q(x,k) := \min -\sum_{i=1}^{B} q_{i} y_{i}^{k} - \sum_{i=1}^{\gamma} s_{j} z_{j}^{k}$$
(3.41)

.t.
$$\mathbf{z}_{j}^{k} = \mathbf{x}_{j} - \sum_{i=1}^{B} \mathbf{m}_{i,j} \mathbf{y}_{i}^{k} \quad \forall \ j = \alpha, \beta, \gamma;$$
 (3.42)

$$\leq y_i^k \leq d_i \quad \forall \ i = A, B; \tag{3.43}$$

$$z_i \ge 0 \quad \forall \ j = \alpha, \beta, \gamma.$$
 (3.44)

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$$0 < v_i^k < d_i \quad \forall i = A, B$$
:

$$0 \leq y_i^n \leq d_i \quad \forall \ i = A, B;$$

$$z_i \ge 0 \quad \forall \ j = \alpha, \beta, \gamma.$$
 (3.44)

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(3.43)

Intuition

■ Recall the master problem:

$$\max x_0 \tag{4.1}$$

s.t.
$$x_0 \in \{x_0 : (x_0, \mathbf{y}) \in G\};$$
 (4.2)

- \blacksquare How can we construct G?
- We know that there are finitely halflines h = 1, 2, ..., H,

$$G := \bigcup_{h=1,2,...,H} \left\{ (x_0, \mathbf{y}) : \mu_0^h x_0 - \mu_0^h f(\mathbf{y}) + \mu^{h^T} F(\mathbf{y}) \le \mu^{h^T} \mathbf{b} \right\}.$$
(4.3)

■ Construct '*G*' iteratively.

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■ Recall the master problem:

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■ Construct '*G*' iteratively.

FEASIBILITY CONCERN

- Say we have a solution \bar{x} ;
- Will the subproblem

$$Q(\mathbf{x}, \xi) := \min \quad \mathbf{q}^{T}(\xi)\mathbf{y}(\xi)$$
s.t.
$$T(\xi)\mathbf{x} + W\mathbf{y}(\xi) = \mathbf{h}(\xi);$$
(4.4)

$$\mathbf{y}(\xi) \succeq 0. \tag{4.6}$$

always be feasible?

Not necessarily.

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$$(4.5)$$

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- Otherwise, $Q(x,\xi)$ can be infeasible;
- Consider the dual of $Q(x, \xi)$;
- Primal infeasible, dual _____;
- Unbounded & infeasible;
- Infeasible: "the stochastic program is not well-formulated";
- Unbounded: the halfline associated with vector $\bar{\mu}$ goes to infinity.

(4.7)

FEASIBILITY CONCERN (CONT.)

- Action: tell the master problem to cuts \bar{x} ;
- Dual of subproblem, with variable μ :

$$\max \ \boldsymbol{\mu}^T \big(h(\xi) - T(\xi) \bar{\boldsymbol{x}} \big)$$

s.t.
$$W^T \mu \leq q(\xi);$$
 (4.8)

- Solve to find the unbounded ray $\bar{\delta}$;
- Add a feasibility cut

$$\bar{\boldsymbol{\delta}}^{T}(\boldsymbol{h}(\xi) - T(\xi)\boldsymbol{x}) \le 0 \tag{4.9}$$

to the mater problem.



OPTIMALITY CONCERN

- Say we have a solution \bar{x} ;
- Will there be another x',

$$Q(\mathbf{x}') \leq Q(\bar{\mathbf{x}})$$
?

Probably.

(4.10)

OPTIMALITY CONCERN

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?

Probably.

(4.10)



OPTIMALITY CONCERN (CONT.)

- How do we find better solutions (improving halflines h)?
- Let $\theta = \mathcal{Q}(\mathbf{x})$;
- Write the master problem as

$$\min \quad \boldsymbol{c}^{\mathsf{T}} \boldsymbol{x} + \boldsymbol{\theta} \tag{4.11}$$

s.t.
$$A\mathbf{x} = \mathbf{b}$$
; (4.12)

$$x \succeq 0, \tag{4.13}$$

Adding the information of the current solution using the dual of subproblems as a cut:

$$\sum p_k \Big(\bar{\boldsymbol{\mu}}_k^T (\boldsymbol{h}(\boldsymbol{\xi}^k) - T(\boldsymbol{\xi}^k) \boldsymbol{x}) \Big) \le \theta. \tag{4.14}$$

OPTIMALITY CONCERN (CONT.)

- In the cut, $\bar{\mu}_k$ is the solution from the dual of subproblems
- The part

$$\bar{\boldsymbol{\mu}}_{k}^{T}(\boldsymbol{h}(\boldsymbol{\xi}^{k}) - T(\boldsymbol{\xi}^{k})\boldsymbol{x}) \tag{4.15}$$

approximates the objective of a subproblem using its dual.

 \blacksquare The variable θ approximate the value of all subproblems for the master problem.

THE L-SHAPED ALGORITHM

Algorithm 1: The L-shaped Algorithm

```
while True do
           Solve the master problem and obtain solution \bar{x}:
          Feasible ← True:
          for k = 1, 2, ..., K do
                 Construct the dual of subproblem using \bar{x} and the ransom variable \mathcal{E}_{k}:
                 Solve the dual problem:
                 if Subproblem Unbounded then
                       Obtain unbounded ray \bar{\delta}:
                        Add cut \bar{\delta}^T(h(\xi) - T(\xi)x) < 0 to the master problem;
                        Feasible ← False:
 10
                       break.
12
                 end
                 if Subproblem Optimal then
                        Obtain the solution \bar{\mu}_{k}:
14
15
                 end
16
          end
          if Feasible then
17
                v \leftarrow \sum_{k} p_{k} \left( \bar{\mu}_{k}^{T} (h(\xi^{k}) - T(\xi^{k}) \bar{\mathbf{x}}) \right);
                 if v > \theta then
                       Add cut \sum_{k} p_{k} \left( \bar{\mu}_{k}^{T} (h(\xi^{k}) - T(\xi^{k}) \mathbf{x}) \right) \leq \theta to the master problem;
20
                 else
                       break:
22
23
                 end
24
          end
25 end
```

RECALL: THE PRODUCTION PROBLEM, TWO-STAGE

Master problem:

$$\min \quad \sum_{i=\alpha}^{\gamma} c_j x_j + \sum_{k=1}^{3} p_k \cdot Q(x,k)$$
 (5.1)

s.t.
$$x_i \ge 0 \quad \forall \ j = \alpha, \beta, \gamma;$$
 (5.2)

■ Subproblems. $\forall k = 1, 2, 3$:

$$Q(x,k) := \min \quad -\sum_{i=A}^{B} q_i y_i^k - \sum_{i=\alpha}^{\gamma} s_j z_j^k$$

$$(5.3)$$

s.t.
$$z_j^k = x_j - \sum_{i=1}^B m_{i,j} y_i^k \quad \forall \ j = \alpha, \beta, \gamma;$$
 (5.4)

$$0 < v_i^k < d_i^k \quad \forall i = A, B$$
:

$$0 \le y_i^{\kappa} \le d_i^{\kappa} \quad \forall \ i = A, B;$$

$$z_i > 0 \quad \forall \ i = \alpha, \beta, \gamma.$$

$$(5.5)$$

DUALIZE THE SUBPROBLEM

- Let λ and μ be the dual variables associated with the constraints;
- Taking the dual, $\forall k = 1, 2, 3$:

$$\max \sum_{j=\alpha}^{\gamma} x_j \lambda_j^k + \sum_{i=A}^{B} d_i^k \mu_i^k$$
 (5.7)

s.t.
$$\sum_{j=\alpha}^{\gamma} m_{i,j} \lambda_j^k + \mu_i^k \le -q_i \quad \forall \ i = A, B;$$
 (5.8)

$$\lambda_j^k \le -\mathbf{s}_j \quad \forall \ j = \alpha, \beta, \gamma;$$
 (5.9)

$$\mu_i^k \le 0 \quad \forall \ i = A, B. \tag{5.10}$$

FEASIBILITY CUTS

- Let $\lambda_i^{k'}$ and $\mu_i^{k'}$ be the unbounded rays associated with the variables;
- The feasibility cut:

$$\sum_{i=0}^{\gamma} x_j \lambda_j^{k'} + \sum_{i=0}^{B} d_i^k \mu_i^{k'} \le 0.$$
 (5.11)

OPTIMALITY CUTS

- Let $\bar{\lambda}_j^k$ and $\bar{\mu}_i^k$ be the optimal solutions;
- The optimality cut:

$$\sum_{k=1}^{3} p_k \cdot \left(\sum_{i=\alpha}^{\gamma} x_j \bar{\lambda}_j^k + \sum_{i=A}^{B} d_i^k \bar{\mu}_i^k \right) \le \theta.$$
 (5.12)

IMPLEMENTATION

■ Python + Gurobi.

Thank You!

Questions?

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