

Decomposition for Network Design

Bernard Gendron*

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EPFL, Lausanne, Switzerland

* CIRRELT and Département d'informatique et de recherche opérationnelle, Université de Montréal, Canada

Outline of lesson 3: Introduction to decomposition methods

Cutting-plane method

Column generation

Column-and-row generation

Lagrangian relaxation

Benders decomposition

Generic MIP model

$$Z(M) = \min cx + fy$$

$$Ax = b$$

$$Bx + Dy \geq e$$

$$Gy \geq h$$

$$x, y \geq 0$$

y integer

- ▶ Hypotheses: M is feasible and bounded

Cutting-plane method

- ▶ Assume that there are “too many” constraints in $Bx + Dy \geq e$
- ▶ Generate a small subset of these
- ▶ Solve the LP relaxation to obtain an optimal solution (\bar{x}, \bar{y})
- ▶ Solve the **separation problem**:
 - 1) determine that no more valid inequalities among $Bx + Dy \geq e$ are violated by (\bar{x}, \bar{y})
 - 2) otherwise, find at least one valid inequality among $Bx + Dy \geq e$ that cuts (\bar{x}, \bar{y})
- ▶ Case 1): stop the algorithm
Case 2): add the valid inequalities to the model
- ▶ Repeat this iterative process until no more cuts are identified
- ▶ This method solves $LP(M)$, but not M ! What should we do?

Cutting-plane method

- ▶ Assume that there are “too many” constraints in $Bx + Dy \geq e$
- ▶ Generate a small subset of these
- ▶ Solve the LP relaxation to obtain an optimal solution (\bar{x}, \bar{y})
- ▶ Solve the **separation problem**:
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- ▶ Case 1): stop the algorithm
Case 2): add the valid inequalities to the model
- ▶ Repeat this iterative process until no more cuts are identified
- ▶ This method solves $LP(M)$, but not M ! What should we do?
- ▶ Branch-and-cut: cutting-plane at every node of the B&B tree

Column generation method

- ▶ Assume that there are “too many” variables in x
- ▶ Generate a small subset of these (just enough to define a basic feasible solution to $LP(M)$)
- ▶ Solve the LP relaxation to obtain an optimal solution (\bar{x}, \bar{y})
- ▶ Solve the **pricing problem**:
 - 1) determine that no more x variables have a negative reduced cost
 - 2) otherwise, find at least one x variable with a negative reduced cost
- ▶ Case 1): stop the algorithm
Case 2): add the columns to the model
- ▶ Repeat this iterative process until no more variables are found
- ▶ This method solves $LP(M)$, but not M ! What should we do?

Column generation method

- ▶ Assume that there are “too many” variables in x
- ▶ Generate a small subset of these (just enough to define a basic feasible solution to $LP(M)$)
- ▶ Solve the LP relaxation to obtain an optimal solution (\bar{x}, \bar{y})
- ▶ Solve the **pricing problem**:
 - 1) determine that no more x variables have a negative reduced cost
 - 2) otherwise, find at least one x variable with a negative reduced cost
- ▶ Case 1): stop the algorithm
Case 2): add the columns to the model
- ▶ Repeat this iterative process until no more variables are found
- ▶ **This method solves $LP(M)$, but not M ! What should we do?**
- ▶ **Branch-and-price**: column generation at every node of the B&B tree

Column-and-row generation method

- ▶ Assume that there are “too many” variables in x and “too many” constraints in $Bx + Dy \geq e$
- ▶ Generate subsets of the x variables and of the constraints in $Bx + Dy \geq e$
- ▶ Solve the LP relaxation to obtain an optimal solution (\bar{x}, \bar{y})
- ▶ Solve the pricing problem to generate new columns
- ▶ Solve the separation problem to obtain new cuts
- ▶ Repeat this iterative process until no more columns or no more cuts are found
- ▶ Branch-and-**price-and-cut**: column-and-row generation at every node of the B&B tree

Lagrangian relaxation

- ▶ $Bx + Dy \geq e$ can be seen as “complicating” constraints
- ▶ Relax them, but instead of dropping them, add them to the objective by associating **Lagrange multipliers** $\alpha \geq 0$ representing penalties associated to their violation

$$Z(LR(\alpha)) = \min cx + fy + \alpha(e - Bx - Dy)$$

$$Ax = b$$

$$Gy \geq h$$

$$x, y \geq 0$$

y integer

- ▶ For any $\alpha \geq 0$, we have $Z(LR(\alpha)) \leq Z(M)$
- ▶ **Prove this property!**

Lagrangian subproblem

$$Z(LR(\alpha)) = \alpha e + Z_x(\alpha) + Z_y(\alpha)$$

$$Z_x(\alpha) = \min(c - \alpha B)x$$

$$Ax = b$$

$$x \geq 0$$

$$Z_y(\alpha) = \min(f - \alpha D)y$$

$$Gy \geq h$$

$$y \geq 0$$

y integer

- ▶ Hypothesis: both problems are bounded

Lagrangian dual

- ▶ The best values for the Lagrange multipliers are obtained by solving the **Lagrangian dual**:

$$Z(LD(M)) = \max_{\alpha \geq 0} Z(LR(\alpha))$$

- ▶ Let $Y = \{y \geq 0 \text{ and integer} \mid Gy \geq h\}$ and recall that $\text{conv}(Y)$ is a polyhedron
- ▶ **Primal interpretation of Lagrangian duality:**

$$Z(LD(M)) = \min cx + fy$$

$$Ax = b$$

$$x \geq 0$$

$$Bx + Dy \geq e$$

$$y \in \text{conv}(Y)$$

- ▶ Show this result by using Minkowski's theorem and LP duality

Lagrangian dual and LP relaxation

- ▶ We know $\text{conv}(Y) \subseteq \bar{Y}$, where $\bar{Y} = \{y \geq 0 \mid Gy \geq h\}$
- ▶ The primal interpretation of Lagrangian duality implies $Z(LD(M)) \geq Z(LP(M))$
- ▶ If the Lagrangian subproblem has the integrality property ($\text{conv}(Y) = \bar{Y}$), then $Z(LD(M)) = Z(LP(M))$
- ▶ Even when this is the case, maybe there is another Lagrangian relaxation such that $Z(LD(M)) \geq Z(LP(M))$
- ▶ Write down the Lagrangian subproblem and the Lagrangian dual if one relaxes the constraints $Ax = b$

Solving the Lagrangian dual by column generation

- ▶ Solve the **master problem** derived from the primal interpretation of Lagrangian duality and Minkowski's theorem:

$$Z(LD(M)) = \min cx + \sum_{k \in K} \lambda_k (fy_k)$$

$$Ax = b$$

$$Bx + \sum_{k \in K} \lambda_k (Dy_k) \geq e$$

$$\sum_{k \in K} \lambda_k = 1$$

$$x \geq 0, \lambda_k \geq 0, k \in K$$

- ▶ Use column generation for this LP with “too many” variables
- ▶ The pricing problem is simply the Lagrangian subproblem

Solving the Lagrangian dual by subgradient optimization

- ▶ $Z(LR(\alpha))$ is continuous and concave (nice), but non-differentiable (ugly) function of α
- ▶ A **subgradient** of $Z(LR(\alpha))$ at $\bar{\alpha}$ is given by $(e - B\bar{x} - D\bar{y})$, where (\bar{x}, \bar{y}) solves the Lagrangian subproblem for $\alpha = \bar{\alpha}$
- ▶ At each iteration, a subgradient method finds a new α by taking a step in the direction of a subgradient
- ▶ Although there are convergence results, this is essentially a heuristic method that is very quick at each iteration
- ▶ Suggestion: use subgradient optimization at the beginning to get “good” Lagrange multipliers, then switch to column generation to get the best possible lower bound

Benders decomposition

- ▶ y can be seen as “complicating” variables
- ▶ Fix them at feasible values \bar{y} , i.e., such that $\bar{y} \in Y = \{y \geq 0 \text{ and integer} \mid Gy \geq h\}$
- ▶ We then have to solve the following LP, called **Benders subproblem**:

$$Z_x(\bar{y}) = \min cx$$

$$Ax = b$$

$$Bx \geq e - D\bar{y}$$

$$x \geq 0$$

- ▶ This problem is bounded (since M is bounded), but not necessarily feasible

Dual of Benders subproblem

$$Z_x(\bar{y}) = \max \pi b + \alpha(e - D\bar{y})$$

$$\pi A + \alpha B \leq c$$

$$\alpha \geq 0$$

- ▶ Let $D = \{(\pi, \alpha) \mid \pi A + \alpha B \leq c, \alpha \geq 0\}$ be the **dual polyhedron**
- ▶ If the Benders subproblem is infeasible, then its dual is unbounded and there exists an extreme ray of D , (π_j, α_j) , such that $\pi_j b + \alpha_j(e - D\bar{y}) > 0$
- ▶ If the Benders subproblem is feasible, then its dual is also feasible and there exists an extreme point of D , (π_k, α_k) , such that $\pi_k b + \alpha_k(e - D\bar{y}) = Z_x(\bar{y})$

Benders reformulation

$$Z(M) = \min_{y \in Y} fy + Z_x(y)$$

$$Z_x(y) = \{\max_{k \in K} (\pi_k b + \alpha_k (e - Dy)) \mid \pi_j b + \alpha_j (e - Dy) \leq 0, j \in J\}$$

- ▶ We can replace $Z_x(y)$ by a variable z and obtain the following MIP:

$$Z(M) = \min_{y \in Y, z} fy + z$$

$$\pi_k b + \alpha_k (e - Dy) \leq z, \quad k \in K$$

$$\pi_j b + \alpha_j (e - Dy) \leq 0, \quad j \in J$$

Solving the Benders reformulation

- ▶ We can solve this **master problem** with “too many” constraints by a cutting-plane method
- ▶ Start by solving a relaxed master problem with no constraints associated to K and J
- ▶ At every iteration, solve the Benders subproblem to derive
 - 1) an extreme point (π_k, α_k) or
 - 2) an extreme ray (π_j, α_j)
- ▶ Case 1): add the **optimality cut** $\pi_k b + \alpha_k (e - Dy) \leq z$
Case 2): add the **feasibility cut** $\pi_j b + \alpha_j (e - Dy) \leq 0$
- ▶ At every iteration, let (\bar{y}, \bar{z}) be the optimal solution to the relaxed master problem and \bar{x} be the optimal solution to the Benders subproblem (if it is feasible)
- ▶ $f\bar{y} + \bar{z} \leq Z(M) \leq f\bar{y} + c\bar{x}$
- ▶ The algorithm stops when $\bar{z} = c\bar{x}$