Integer Programming
ISE 418

Lecture 20

Dr. Ted Ralphs

Reading for This Lecture

- Wolsey, Chapters 10 and 11
- Nemhauser and Wolsey Sections II.3.1, II.3.6, II.3.7, II.5.4
- CCZ Chapter 8
- “Decomposition in Integer Programming,” Ralphs and Galati.
- “Selected Topics in Column Generation,” Lübbecke and Desrosiers

Review: Setting

We divide the constraints into two set and use the following notation to refer to various relaxations of the original feasible region.

$$\begin{aligned} \max\ & c^\top x \\ \text{s.t. } & A'x \le b' \text{ (the "nice" constraints)} \\ & A''x \le b'' \text{ (the "complicating" constraints)} \\ & x \in \mathbb{Z}^n \end{aligned} \tag{MILP-D}$$

$$\begin{aligned} \mathcal{Q}' &= \{x \in \mathbb{R}^n \mid A'x \le b'\}, \\ \mathcal{Q}'' &= \{x \in \mathbb{R}^n \mid A''x \le b''\}, \\ \mathcal{Q} &= \mathcal{Q}' \cap \mathcal{Q}'', \\ \mathcal{S} &= \mathcal{Q} \cap \mathbb{Z}^n, \text{ and} \\ \mathcal{S}_R &= \mathcal{Q}' \cap \mathbb{Z}^n. \end{aligned}$$

Review: The Decomposition Bound

By exploiting our knowledge of $\text{conv}(\mathcal{S}_R)$, we wish to compute the so-called *decomposition bound* by *partial convexification*.

$$z_{\text{D}} = \max_{x \in \text{conv}(\mathcal{S}_R)} \left\{ c^\top x \mid A'' x \geq b'' \right\}$$

$$z_{\text{IP}} \leq z_{\text{D}} \leq z_{\text{LP}}$$

This can be done using three different basic approaches:

- Dantzig-Wolfe decomposition (dynamic generation of extreme points of $\text{conv}(\mathcal{S}_R)$)
- Lagrangian relaxation (dynamic generation of extreme points of $\text{conv}(\mathcal{S}_R)$)
- Cutting plane method (dynamic generation of facets of $\text{conv}(\mathcal{S}_R)$).

Dantzig-Wolfe Decomposition

- In this technique, we utilize the fact that every point in $\mathrm{conv}(\mathcal{S}_R)$ can be written as the convex combination of extreme points of $\mathrm{conv}(\mathcal{S}_R)$.
- Here is the Dantzig-Wolfe LP:

$$
\begin{aligned}
\max \quad & c^\top x \\
\text{s.t.} \quad & \sum_{s \in \mathcal{E}} \lambda_s s = x \\
& A'' x \leq b'' \\
& \sum_{s \in \mathcal{E}} \lambda_s = 1 \\
& \lambda \in \mathbb{R}_+^{\mathcal{E}}
\end{aligned}
\qquad \text{(DWLP)}
$$

  where $\mathcal{E}$ is the set of extreme points of $\mathrm{conv}(\mathcal{S}_R)$.

- As we observed previously, if we enforce integrality of x, this is a reformulation of the IP.
- This is a relaxation of (MILP-D); solving yields an upper bound on z_{DW}.
- Typically, x is not explicitly present in the formulation.

Dantzig-Wolfe LP

We can rewrite the Dantzig-Wolfe LP in the following two forms

$$
\begin{aligned}
\max\ & c^\top \left(\sum_{s \in \mathcal{E}} s \lambda_s \right) \\
\text{s.t.}\ \ & A'' \left(\sum_{s \in \mathcal{E}} s \lambda_s \right) \le b'' \\
& \sum_{s \in \mathcal{E}} \lambda_s = 1 \\
& \lambda \in \mathbb{R}_+^{\mathcal{E}}
\end{aligned}
$$

$$
\begin{aligned}
\max\ & \sum_{s \in \mathcal{E}} (c^\top s) \lambda_s \\
\text{s.t.}\ \ & \sum_{s \in \mathcal{E}} (A'' s) \lambda_s \le b'' \\
& \sum_{s \in \mathcal{E}} \lambda_s = 1 \\
& \lambda \in \mathbb{R}_+^{\mathcal{E}}
\end{aligned}
$$

Solving the Dantzig-Wolfe LP

- We solve this Dantzig-Wolfe LP (often called the *master problem*) using column generation.
- We begin with a restricted set of columns generated heuristically.
  - Start with a subset of "promising" columns.
  - Solve the *restricted master problem* (RMP) with just these columns.
  - *Price* the remaining columns and add those with positive reduced costs.
  - Iterate.

The Dantzig-Wolfe Subproblem

- In Dantzig-Wolfe, we have a column for each member of $\mathcal{E}$.
- For $s \in \mathcal{E}$, if we take

$$\begin{aligned} c_s &= c^\top s \\ A_s &= A'' s, \end{aligned}$$

then the reduced cost of the column associated with s is

$$c_s - (uA_s + \alpha) = c^\top s - u(A''s) - \alpha = (c^\top - uA'')s - \alpha,$$

where α is the dual multiplier on the convexity constraint and u is a vector of dual multipliers associated with the other constraints.

- Since α is a constant with respect to this subproblem, the column generation subproblem is

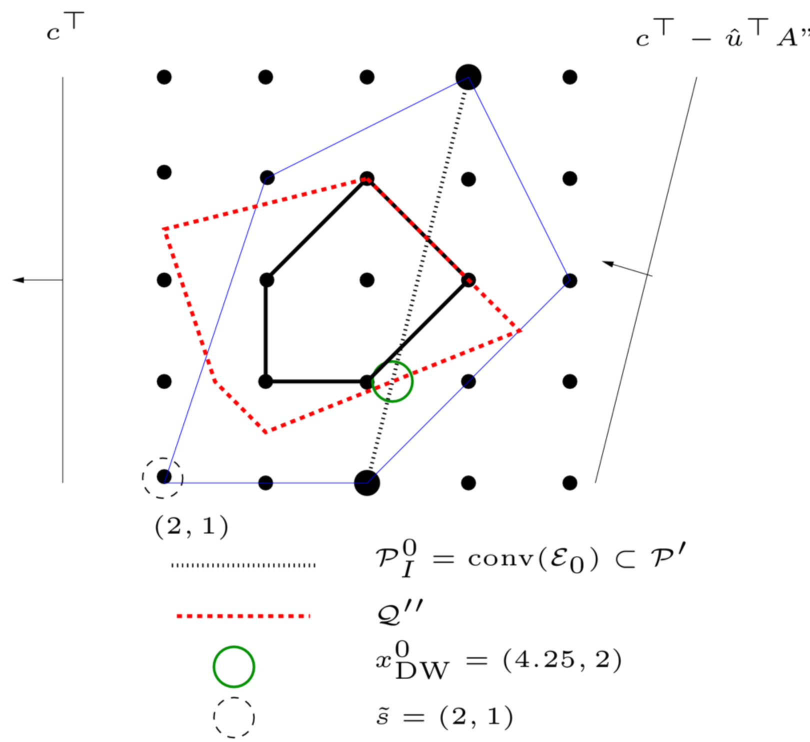
$$LR(u) : z_{LR}(u) = -\alpha + \max_{x \in \mathcal{S}_R} \{(c - uA'')x\},$$

which is equivalent to the Lagrangian relaxation!

Geometry of Dantzig-Wolfe Decomposition

DW utilizes an *inner* approximation of $\mathrm{conv}(\mathcal{S}_R)$

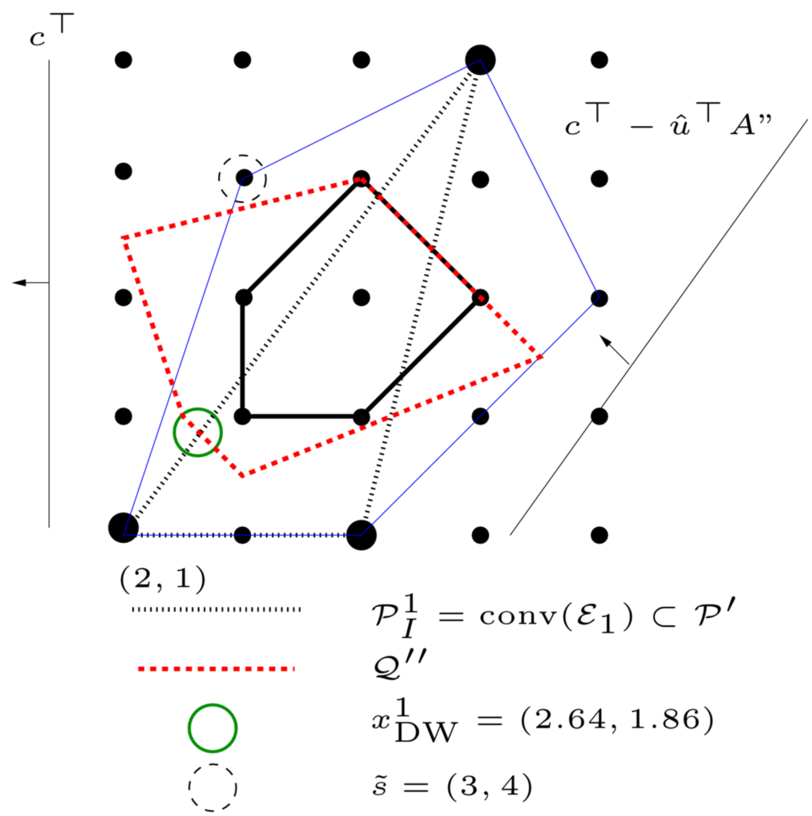
- **Master**:
  $z_{\mathrm{DW}} = \max_{\lambda \in \mathbb{R}_+^{\mathcal{E}}} \left\{ c^\top \left(\sum_{s \in \mathcal{E}} s \lambda_s \right) \mid A'' \left(\sum_{s \in \mathcal{E}} s \lambda_s \right) \leq b'', \sum_{s \in \mathcal{E}} \lambda_s = 1 \right\}$
- **Subproblem**: $LR(c^\top - uA'')$



Geometry of Dantzig-Wolfe Decomposition

DW utilizes an *inner* approximation of $\mathrm{conv}(\mathcal{S}_R)$

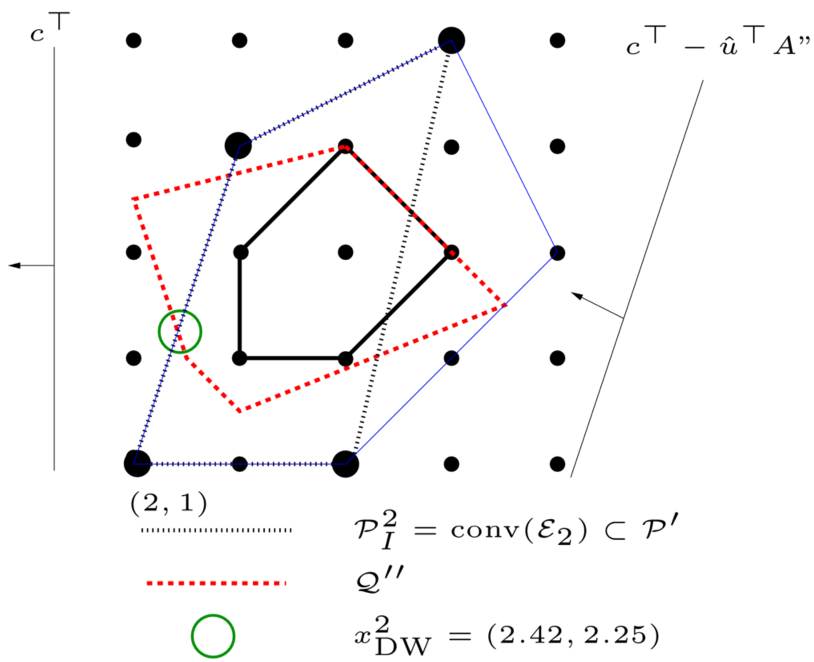
- **Master**:
  $z_{\mathrm{DW}} = \max_{\lambda \in \mathbb{R}_+^{\mathcal{E}}} \left\{ c^\top \left(\sum_{s\in\mathcal{E}} s\lambda_s\right) \mid A'' \left(\sum_{s\in\mathcal{E}} s\lambda_s\right) \le b'', \sum_{s\in\mathcal{E}} \lambda_s = 1 \right\}$
- **Subproblem**: $LR(c^\top - uA'')$



Geometry of Dantzig-Wolfe Decomposition

DW utilizes an *inner* approximation of $\mathrm{conv}(\mathcal{S}_R)$

- **Master**:
  $z_{\mathrm{DW}} = \max_{\lambda \in \mathbb{R}_+^{\mathcal{E}}} \left\{ c^\top \left(\sum_{s \in \mathcal{E}} s\lambda_s \right) \;\middle|\; A'' \left(\sum_{s \in \mathcal{E}} s\lambda_s \right) \leq b'', \sum_{s \in \mathcal{E}} \lambda_s = 1 \right\}$
- **Subproblem**: $LR(c^\top - uA'')$



Block Structure and Dantzig-Wolfe

- When the problem has block structure, the single subproblem may decompose into independent blocks.
- In this case, we can use a separate convexity constraint for each block.
- There are many common cases in which the blocks are identical (e.g., VRP with homogeneous fleet).
  - In such a case, the separate convexity constraint can be aggregated and the relaxation effectively collapses to a single block.
  - We end up with a convexity constraints, but with right-hand side K, where K is the number of blocks.
  - Note that in this case, the original model exhibits symmetry that makes standard solution method ineffective.
  - Dantzig-Wolfe decomposition is one way of combatting this.
  - In a future lecture, we will discuss other methods of handling symmetry in MILPs.

Example: The Generalized Assignment Problem

- The problem is to assign m tasks to n machines subject to capacity constraints.
- An IP formulation of this problem is

$$
\begin{aligned}
\max \ & \sum_{i=1}^{m}\sum_{j=1}^{n} p_i^j x_{ij} \\
s.t. \ & \sum_{j=1}^{n} x_{ij} = 1, \qquad i = 1,\ldots,m, \\
& \sum_{i=1}^{m} w_{ij} x_{ij} \le d_j, \qquad j = 1,\ldots,n, \\
& x_{ij} \in \{0,1\}, i = 1,\ldots,m, j = 1,\ldots,n,
\end{aligned}
$$

- The variable x_{ij} is one if task i is assigned to machine j.
- The "profit" associated with assigning task i to machine j is p_{ij}.

Applying Dantzig-Wolfe to the GAP

- Let's naively apply Dantzig-Wolfe to the GAP.
- Note that if we relax the constraint that each item be assigned to a different machine, the problem decomposes by machine.
- This allows us to use a separate convexity constraint for each machine.
- Then the Dantzig-Wolfe LP is

$$
\begin{aligned}
\max \sum_{j=1}^{n} \sum_{s \in \mathcal{E}_j} \lambda_s^j \left[\sum_{i=1}^{m} p_i^j s_i \right] & \\
s.t. \quad \sum_{j=1}^{n} \sum_{s \in \mathcal{E}_j} \lambda_s^j s_i &= 1, \quad i = 1, \ldots, m, \\
\sum_{s \in \mathcal{E}_j} \lambda_s^j &= 1, \quad j = 1, \ldots, n, \\
\lambda^j \in \mathbb{R}_+^{\mathcal{E}_j}&, j = 1, \ldots, n,
\end{aligned}
$$

where $\mathcal{E}^j$ is the set of extreme points for the knapsack polytope associated with machine j.

Applying Dantzig-Wolfe to the GAP (cont.)

- In the previous slide, the columns are subsets of the tasks that can be assigned to one particular machines (called *assignments*).
- For assignment $s \in \mathcal{E}^j$, $s_i = 1$ if task i is assigned to machine j.
- The relaxation problem itself decomposes into a set of independent knapsack problems.
- Note that one feasible assignment is to assign no tasks, which would correspond to a column of all zeros.
- Therefore, we could also write the convexity constraints as inequalities.
- Finding an initial feasible set of columns is trivial.
- Note that the master problem is a relaxation of a set partitioning problem.

Aggregating

- Now consider the case when
  - $p = p_{i1} = p_{i2} = \cdots = p_{in}$ for all $i = 1, \ldots m$ and
  - $w = w_{i1} = w_{i2} = \cdots = w_{in}$ for all $i = 1, \ldots m$.
- In this case, we have that $\mathcal{E} = \mathcal{E}_1 = \mathcal{E}_2 = \cdots = \mathcal{E}_j$ for all $i, j \in 1, dots, n$.
- Then we can aggregate as follows.

$$
\begin{aligned}
\max \sum_{s \in \mathcal{E}} \lambda_s \left[p^\top s\right] & \\
s.t. \quad \sum_{i=1}^{n} \sum_{s \in \mathcal{E}} \lambda_s s_i = 1, & \quad i = 1, \ldots, m, \\
\sum_{s \in \mathcal{E}} \lambda_s = K, & \quad j = 1, \ldots, n, \\
\lambda \in \mathbb{R}_+^{\mathcal{E}} &
\end{aligned}
$$

Review: Lagrangian Relaxation

- We continue with the same setup.

$$\begin{aligned} \max\ & c^\top x \\ \text{s.t. } & A'x \le b' \text{ (the ``nice'' constraints)} \\ & A''x \le b'' \text{ (the ``complicating'' constraints)} \\ & x \in \mathbb{Z}^n \end{aligned} \qquad \text{(MILP-D)}$$

where optimizing over $\mathcal{S}_R = \{x \in \mathbb{Z}^n \mid A'x \le b'\}$ is "easy."

- Lagrangian Relaxation (for $u \ge 0$):

$$LR(u) : z_{LR}(u) = ub'' + \max_{x \in \mathcal{S}_R} \{(c^\top - uA'')x\}.$$

The Lagrangian Dual

- The next step is to obtain a dual problem formed by allowing u to vary.
- We are looking for the value of $u \geq 0$ that yield the lowest upper bound.
- The Lagrangian dual problem, LD, is

$$z_{LD} = \min_{u \geq 0} z_{LR}(u)$$

- The Lagrangian dual can be rewritten as the following LP

$$z_{LD} = \min_{\eta, u} \{\alpha + ub'' \mid \alpha \geq (c^\top - uA'')s, s \in \mathcal{E}, u \geq 0\}$$

- This is exactly the LP dual of (DWLP)!
- Solving it using a cutting plane algorithm is equivalent to solving (DWLP) by column generation.
- The separation problem is again $LR(u)$!

Solving the Lagrangian Dual with Subgradient Optimization

- Note that $(c^\top - uA'')^\top x$ is an affine function of u for a fixed x.
- This tells us that $z_{LR}(u)$, when viewed as a function of u, is the maximum of a finite number of affine functions.
- Hence, it is piecewise linear and convex on the domain over which it is finite.
- We can easily minimize any convex function which we can evaluate and subdifferentiate using a technique called *subgradient optimization*.
- This is just a variant of gradient descent
- In each iteration, we move in the direction of the negative gradient, which is just the degree of violation of each constraint.
- There are a wide range of implementations of this basic idea.

Textbook Subgradient Algorithm

- The idea of the subgradient algorithm is to first fix u and determine x by optimizing over $\mathcal{S}_R$.
- Then update u according to the observed violations.
- Here is a basic *subgradient algorithm* for solving the Lagrangian dual:
  1. Choose initial Lagrange multipliers $u^0 \geq 0$ and set $t = 0$.
  2. Solve the Lagrangian subproblem $LR(u^t)$ to obtain x^t.
  3. Calculate the current violation of the complicating constraints $\gamma^t = b'' - A''x^t$.
  4. Set $u_j^{t+1} \leftarrow \max\{u_j^t - \theta^t\gamma^t, 0\}$ where θ^t is the chosen *step size*.
  5. Set $t \leftarrow t + 1$ and go to step 2.
- This algorithm is guaranteed to converge to the optimal solution as long as $\{\theta^t\}_{t=0}^{\infty} \rightarrow 0$ and $\sum_{t=0}^{\infty} \theta^t = \infty$, e.g., harmonic series.
- In practice, one usually uses a geometric progression for the step sizes.
- Sometimes, it's difficult to know when the optimal solution has been reached.

Performing the Updates

- Suppose we have an estimate $\bar{L}$ of the optimal value.
- We can choose u^{t+1} such that the Lagrangian objective of x^t is $\bar{L}$.
- Since we have that $u^{t+1} = u^t - \theta_k \gamma^t$ (in the equality constrained case), then this means

$$\begin{aligned} u^{t+1}b'' + (c^\top - u^{t+1}A'')x^t &= c^\top x^t + u^{t+1}\gamma^t \\ &= c^\top x^t + [u^t - \theta_t \gamma^t]\gamma^t \\ &= \bar{L} \end{aligned}$$

- Finally, solving and putting it all together, we obtain

$$\theta_t = \frac{L(u^t) - \bar{L}}{\|\gamma^t\|^2}$$

Performing the Updates (cont.)

- Since we do not usually know a good value for the new target, we can instead use the value L of the best known solution.
- We also scale by a small factor that we reduce as the algorithm progresses.
- We then finally have

$$\theta_t = \frac{\alpha^t [L(u^t) - L]}{\|\gamma^t\|^2}$$

- Here α^t is an additional factor used to reduce the step size over time.
- Typically, we start with $\alpha^0 = 2$ and reduce α^t by half when the Lagrangian objective does not improve for a specified number of iterations.

Example: Knapsack Problem

- We consider a binary knapsack problem $\max_{x \in \mathbb{B}^n}\{c^\top x \mid a^\top x \leq b\}$ for $a, c \in \mathbb{Z}^n_+$ and $b \in \mathbb{Z}_+$.
- If we relax the knapsack constraint, we have only bound constraints left.
- The relaxation can be solved by setting variables with positive coefficient to upper bounds and variables with negative coefficients to lower bound.
- Thus,

$$LR(u) = \sum_{i=1}^{n} \max\{0, c_i - ua_i\} + ub \tag{1}$$

- Note that the feasible region in this case has all integral extreme points, so $z_{LD} = z_{LP}$.

Example: Knapsack Problem (cont.)

- Let us assume from here on that the variables are arranged in non-increasing order by the ratio c_i/a_i.
- Under this assumption, we can rewrite (1) equivalently as:

$$LR(u) = \sum_{i=j}^{n} c_i + u(b - \sum_{i=j}^{n} a_i) \tag{2}$$

where $j = \text{argmin}\{i \mid c_i - ua_i \geq 0\} = \text{argmin}\{i \mid c_i/a_i \geq u\}$.

- We know $LR(u)$ will be minimized when it has a zero subgradient, which will occur for $u = c_k/a_k$, where $\sum_{i=k}^{n} a_i \leq b \leq \sum_{i=k-1}^{n} a_i$.
- Note that this optimal solution is exactly the same as the optimal dual solution to the LP relaxation, derived from LP duality.

Example: Knapsack Problem (cont.)

- Let us now consider an instance with $n = 3$ described by the data $a = [3\ 1\ 4]$, $c = [10\ 4\ 14]$, and $b = 4$.
- Since the cost vector c is non-negative, the first solution will be to choose all items, i.e., set all variables to value 1.
- We take the step sizes to be a simple geometric sequence.
- Then we have $u_1 = u_0 - \theta_0\gamma_0 = \sum_{i=1}^{n} a_i - b$.
- Here is the sequence of iterates:

t	x^t	γ_t	u_t	θ_t
0	$[1\ 1\ 1]$	-4	0	1
1	$[0\ 1\ 0]$	3	4	$\frac{1}{2}$
2	$[1\ 1\ 1]$	-4	$\frac{5}{2}$	$\frac{1}{4}$
3	$[0\ 1\ 1]$	-1	$\frac{7}{2}$	$\frac{1}{8}$
4	$[0\ 1\ 0]$	3	$\frac{29}{8}$	$\frac{1}{16}$
5	$[0\ 1\ 1]$	-1	$\frac{55}{16}$	$\frac{1}{32}$
6	$[0\ 1\ 1]$	-1	$\frac{111}{32}$	$\frac{1}{64}$

- The same solution is now repeated and the sequence will converge to the optimal value of $7/2$.

Example: Knapsack Problem (cont.)

- Note that the optimal solution was reached in the fourth iteration on the previous slide, but this was prior to convergence.
- The sequence above is not unique because there is an alternative optimal solution to the Lagrangian subproblem in iteration 3.
- Here is an alternative sequence:

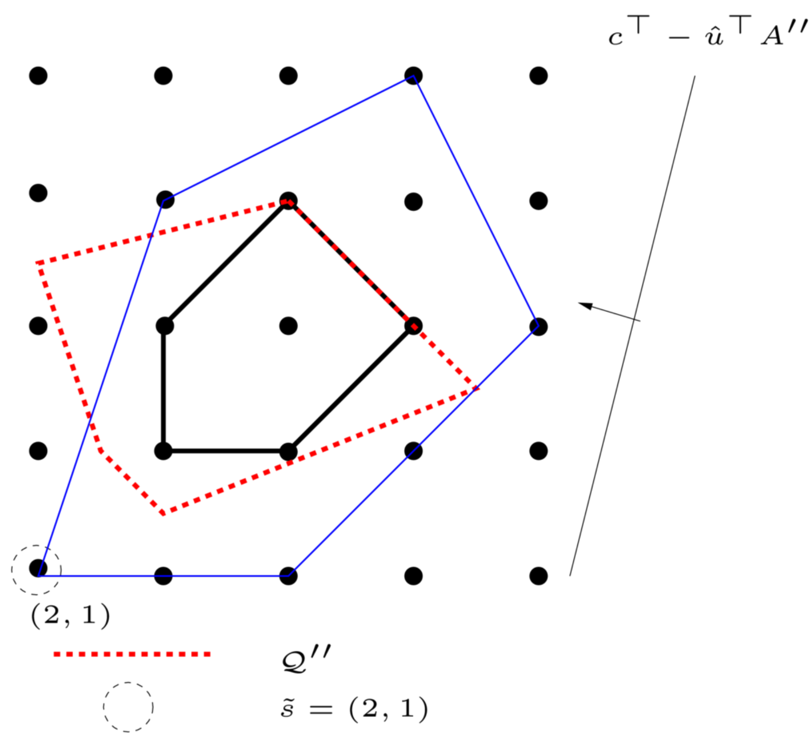
t	x^t	γ_t	u_t	θ_t
0	[1 1 1]	-4	0	1
1	[0 1 0]	3	4	$\frac{1}{2}$
2	[1 1 1]	-4	$\frac{5}{2}$	$\frac{1}{4}$
3	[1 1 1]	-4	$\frac{7}{2}$	$\frac{1}{8}$
4	[0 1 0]	3	4	$\frac{1}{16}$
5	[0 1 0]	3	$\frac{61}{16}$	$\frac{1}{32}$
6	[0 1 0]	3	$\frac{119}{32}$	$\frac{1}{64}$

- This sequence will converge to $29/8 = 3.625$ rather than to the optimum.
- This is because our sequence of step sizes goes to zero too quickly.
- If we use a harmonic series, we should get conergence (modulo possible numerical issues related to round-off, etc.).

Geometry of the Lagrangian Dual

LD iteratively produces single extreme points of $\text{conv}(\mathcal{S}_R)$ and uses the violation of the relaxed constraints to adjust the dual solution.

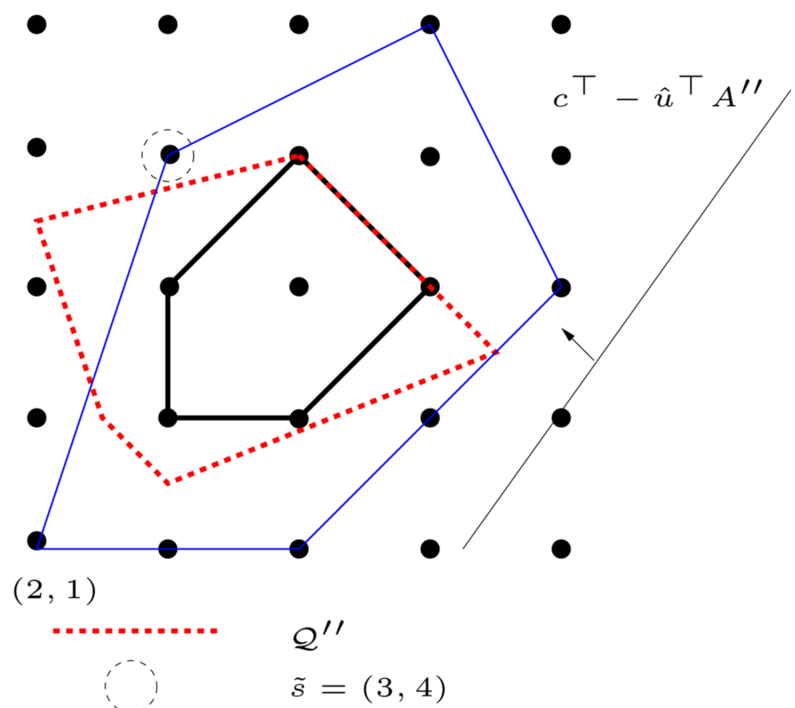
- **Master**: $z_{\text{LD}} = \min_{u \in \mathbb{R}_+^{m''}} \left\{ \max_{s \in \mathcal{E}} \left\{ c^\top s + u^\top (b'' - A''s) \right\} \right\}$
- **Subproblem**: $\text{LR}(c^\top - uA'')$



Geometry of the Lagrangian Dual

LD iteratively produces single extreme points of $\text{conv}(\mathcal{S}_R)$ and uses the violation of the relaxed constraints to adjust the dual solution.

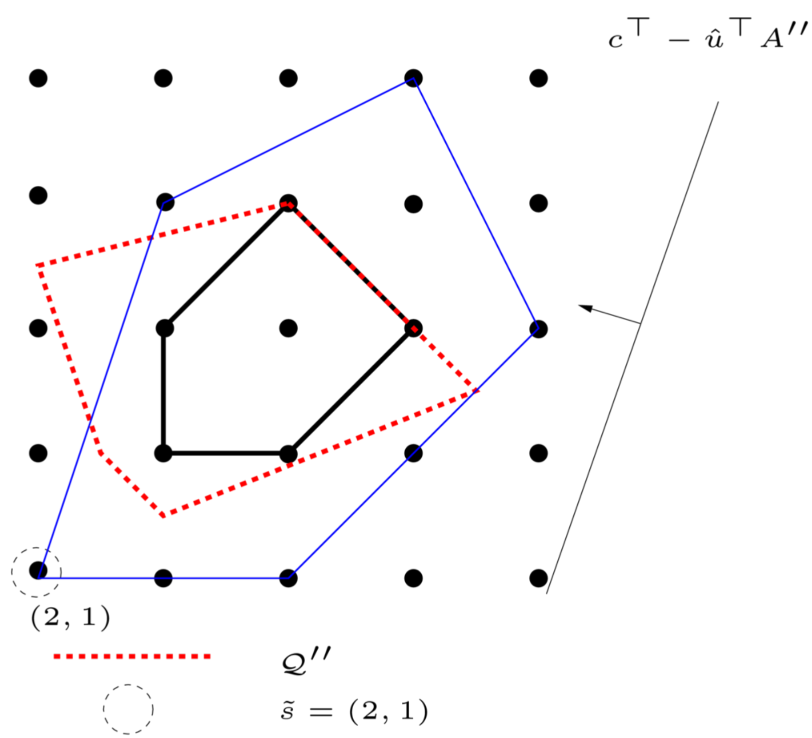
- **Master**: $z_{\text{LD}} = \min_{u \in \mathbb{R}^{m''}_{+}} \left\{ \max_{s \in \mathcal{E}} \left\{ c^\top s + u^\top (b'' - A'' s) \right\} \right\}$
- **Subproblem**: $\text{LR}(c^\top - uA'')$



Geometry of the Lagrangian Dual

LD iteratively produces single extreme points of $\mathrm{conv}(\mathcal{S}_R)$ and uses the violation of the relaxed constraints to adjust the dual solution.

- **Master**: $z_{\mathrm{LD}} = \min_{u \in \mathbb{R}^{m''}_+} \left\{ \max_{s \in \mathcal{E}} \left\{ c^\top s + u^\top (b'' - A'' s) \right\} \right\}$
- **Subproblem**: $\mathrm{LR}(c^\top - uA'')$



The Cutting Plane Method as a Decomposition Method

- Finally, it is possible to exploit our ability to optimize over $\mathcal{S}_R$ in a more traditional cutting plane method.
- Recall the algorithm for separating using an optimization oracle from Lecture 12.
- We can use this algorithm as a means of separating (possibly infeasible) solutions from $\mathcal{S}_R$ in the context of a cutting plane method.

Lagrange Cuts

- Boyd observed that for $u \in \mathbb{R}^m_+$, a *Lagrange cut* of the form

$$(c - uA'')^\top x \leq LR(u) - ub'' \qquad \text{(LC)}$$

is valid for $\mathcal{P}$.

- If we take u^* to be the optimal solution to the Lagrangian dual, then this inequality reduces to

$$(c - u^*A'')^\top x \leq z_D - ub'' \qquad \text{(OLC)}$$

- If we now take

$$x^D \in \operatorname{argmax} \left\{ c^\top x \mid A''x \leq b'', (c - u^*A'')^\top x \geq z_D - ub'' \right\},$$

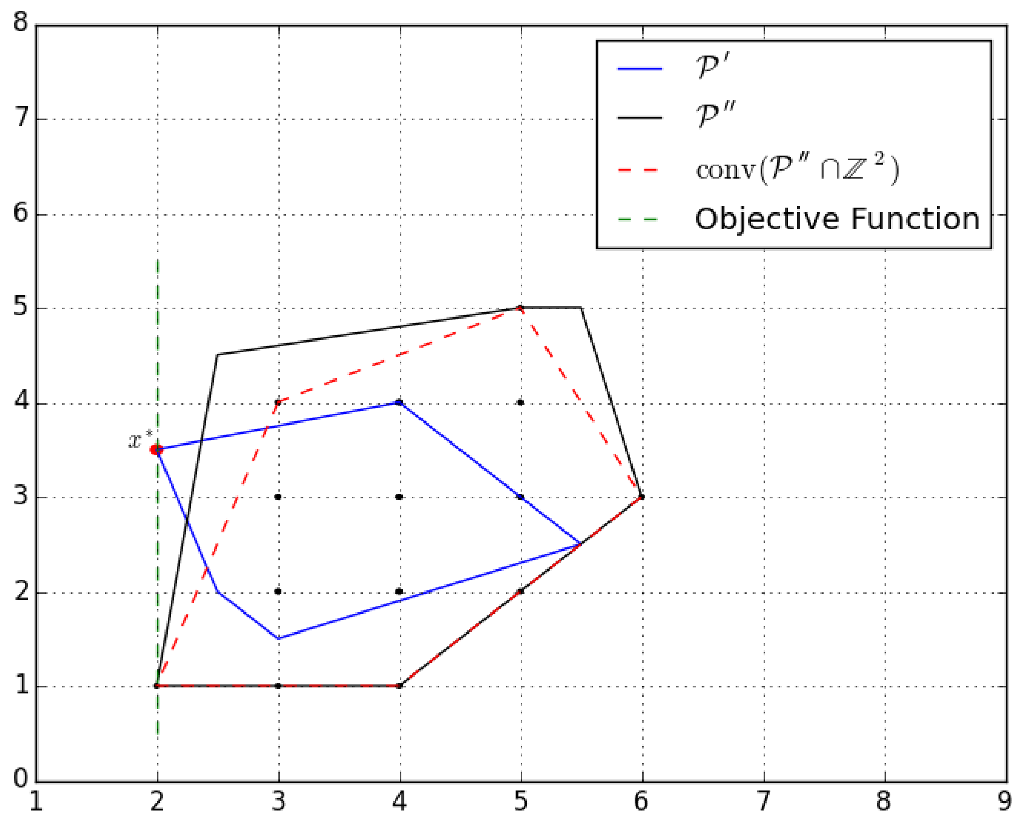
then we have $c^\top x^D = z_D$.

- Such cuts can be generated using an optimization-based oracle.

Geometry of the Cutting Plane Method

CPM utilizes an optimization-based oracle to separate from $\mathrm{conv}(\mathcal{S}_R)$

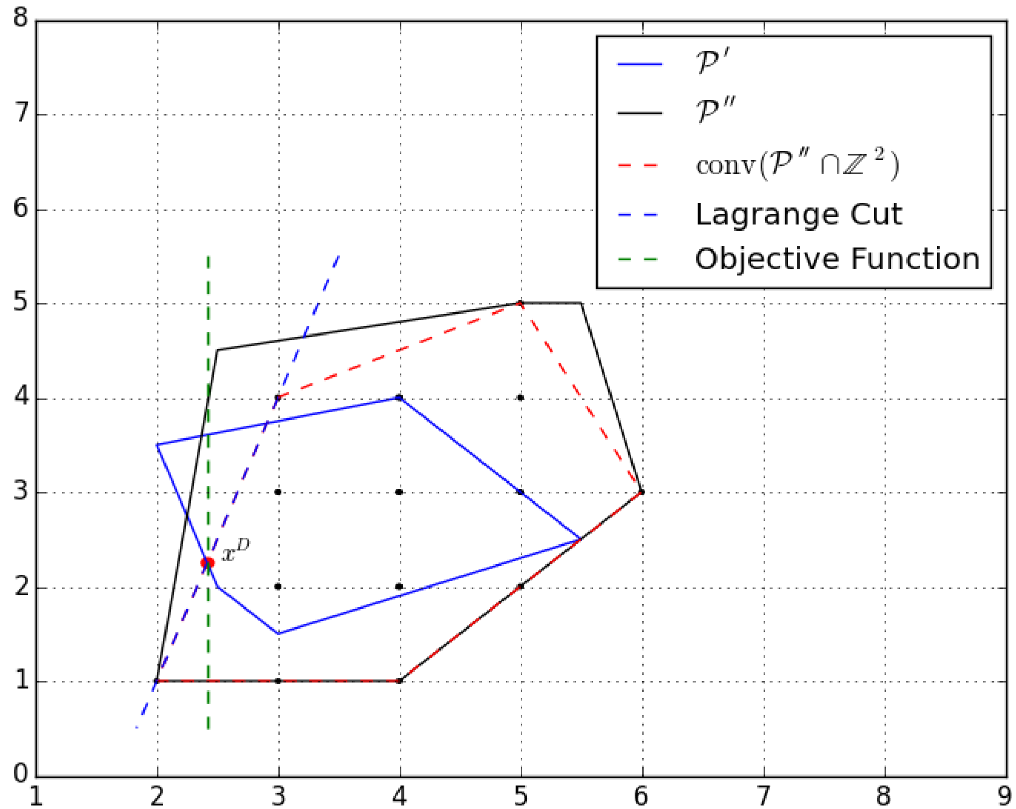
- **Master**:
  $z_{\mathrm{CP}} = \max_{x \in \mathbb{R}^n_+} \left\{ c^\top x \mid A''x \leq b'', (\alpha^k)^\top x \leq \beta^k, 1 \leq k \leq L \right\}$
- **Subproblem**: $OPT(S_R)$



Geometry of the Cutting Plane Method

CPM utilizes an optimization-based oracle to separate from $\text{conv}(\mathcal{S}_R)$

- **Master**:
  $z_{\text{CP}} = \max_{x \in \mathbb{R}^n_+} \{c^\top x \mid A''x \leq b'', (\alpha^k)^\top x \leq \beta^k, 1 \leq k \leq L\}\}$
- **Subproblem**: $OPT(S_R)$



Comparing the Methods

- Recall that the Lagrangian dual can be rewritten as the following LP

$$z_{LD} = \min_{\eta,u}\{\eta + ub'' \mid \eta \geq (c^\top - uA'')s, s \in \mathcal{E}, u \geq 0\}$$

- It is easy to show that this LP is the dual of the Dantzig-Wolfe LP.
- Thus, both these method produce the same bound (in principle).

$$z_D = z_{LD} = z_{DW}$$

- The cutting plane method just described is yet another method for computing the same bound.
- In practice, there are great differences between these three methods, both algorithmically and numerically.
  - Conceptually, the Lagrangian dual produces only a dual solution and does not include any explicit primal solution information.
  - The Dantzig-Wolfe LP produces a primal solution, which can be used to perform generate valid inequalities and tighten the relaxation.
- Naive implementations are slow to converge and numerical difficulties may prevent the calculation of an exact bound.

Choosing a Decomposition

- Typically, there are multiple choices for decomposing a give IP.
- The definition of the set $\mathcal{S}_R$ determines the strength of the bound.
- However, it is important to choose a relaxation that can be solved relatively easily (but not too easily).
- The relaxation must be solved iteratively in order to solve the Lagrangian dual.
- Recall the TSP example.
- Other Examples
  - Flow Problem with Budget Constraints
  - Facility Location Problem
  - Generalized Assignment Problem

Comparing Decomposition-based Bounding to LP-based Bounding

- The class of methods we have just discussed are called *decomposition-based methods* because they decompose the problem into two parts.
- Up until the mid-1970's, these methods were very popular for solving integer programming problems.
- They can effectively strengthen the bound obtained by LP relaxation alone.
- However, after methods based on strengthening the LP relaxation using valid inequalities were introduced, they fell out of favor.
- It is possible to combine these two approaches.
- This is one of the current frontiers of research in integer programming.