

Tutorial 10: Solving Cutting Stock Problem Using Column Generation Technique

GIAN Short Course on Optimization: Applications, Algorithms, and Computation

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Linear Program in standard form:

Minimize
$$c^T x$$
,
Subject to $Ax = b$,
 $x \ge 0$.

- \mathcal{P} is the corresponding feasible set, matrix $A_{m \times n}$ has full row rank
- A_j is the j^{th} column of the matrix A.
- x be a 'basic' feasible solution and $B(1), \ldots, B(m)$ be the indices of basic variables.
- $NB = \{NB(1), ..., NB(n-m)\}$ be the indices of nonbasic variables.
- $B = [A_{B(1)} \dots A_{B(m)}]$ is basis matrix and $N = [A_{NB(1)} \dots A_{NB(n-m)}]$ be the nonbasis matrix.

Optimality conditions

• Vector $x_N = (x_{NB(1)}, \dots, x_{NB(n-m)})$ for nonbasic variables is **0** and vector $x_B = (x_{B(1)}, \dots, x_{B(m)})$ of basic variables is obtained as

$$Ax = \begin{bmatrix} B \ N \end{bmatrix}^T \begin{bmatrix} x_B \\ x_N \end{bmatrix} = b,$$

$$Bx_B + Nx_N = b,$$

$$x_B = B^{-1}b.$$

Consider moving away from x to $x + \theta d^j$, $\theta > 0$ by selecting a nonbasic variable x_i , $j \in N$.

Algebraically,
$$d_j^j = 1$$
 and $d_i^j = 0, \forall i \in NB, i \neq j$. x_B becomes $x_B + \theta d_B^j$, where $d_B^j = \left(d_{B(1)}^j, \dots, d_{B(m)}^j\right)$

For feasibility, $A(x + \theta d^j) = b$ and

$$Ad^{j} = Bd_{B}^{j} + Nd_{N}^{j} = 0,$$

$$Bd_{B}^{j} + A_{j} = 0,$$

$$d_{B}^{j} = -B^{-1}A_{j}.$$

Objective value at the new point is $c^T(x + \theta d^j)$ and per unit change along basic direction d^j (reduced cost of nonbasic variable x_j) is

$$\overline{c}_j = c^T d^j = c_j - c_B^T B^{-1} A_j$$

Theorem (Optimality conditions)

Consider a basic feasible solution x associated with a matrix B, and let \overline{c} be the corresponding vector of reduced costs. If $\overline{c} \geq 0$, then x is optimal.

Column Generation

Motivation:

- Column generation first suggested in the context of multi-commodity network flow problem (Ford and Fulkerson, 1958).
- Dantzig and Wolfe (1960) adapted it to LP with a decomposable structure.
- Gilmore and Gomory (1961) demonstrated its effectiveness in a cutting stock problem.
- Other applications: Vehicle routing, crew scheduling, integer-constrained problems etc.

Column Generation

Recall

- number of nonzero variables (basic variables) is equal to the number of constraints.
- Hence even though the number of possible variables (columns) may be large, we only need a small subset of these (in basis B) in the optimal solution.

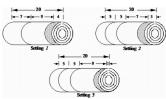
Crucial insight

 If a problem has many variables (or columns) but fewer constraints, work with a partial A matrix.



Example: Cutting Stock Problem





Size of the item demanded	5-ft	7-ft	9-ft
Number of items demanded	25	20	15

- Width of standard stock is 20 feet.
- Demand is met by cutting up standard stocks into items of required widths (refer figure).
- Objective is to minimize the number of standard stocks to meet the customer demands.

Cutting Stock Problem (CSP)

Problem description:

- Stock width W_S , and a set of items \mathcal{I} .
- Width of items denoted by w_i , and their demand d_i .
- Cost of using a stock per unit width is 1
- ullet Set of cutting patterns ${\cal P}$
- a_{ip} : number of pieces of item $i \in \mathcal{I}$ cut in pattern $p \in \mathcal{P}$
- Minimize total cost (number of stocks used)

Decision variables:

• $x_p \in \mathcal{P}$: number of times a cutting pattern p is used

Mathematical formulation (master)

Objective: Minimize total cost

$$\mathsf{Min} \ \sum_{i \in \mathcal{P}} \mathsf{x}_p,$$

Constraints

Demand of each item must be fulfilled

$$\sum_{p\in\mathcal{P}}a_{ip}x_p>=d_i,\quad\forall i\in\mathcal{I},$$

Non-negativity and integrality constraints

$$x_p \in \mathbb{Z}_+, \quad \forall p \in \mathcal{P}.$$

Check:

$$\sum_{i\in\mathcal{I}}a_{ip}w_i <= W_{\mathcal{S}}. \quad \forall p\in\mathcal{P},$$

The Knapsack (sub) Problem

Problem description:

- ullet Pick a new 'pattern' from ${\cal P}$ with most negative 'reduced cost'
- 'Value' of item v_i , $i \in \mathcal{I}$ (multiplier of demand constraint)

Decision variables:

• $u_i \in \mathcal{I}$: number of times an item i is cut in the (new) pattern Objective: Minimize reduced cost

$$\mathsf{Min} \ 1 - \sum_{i \in \mathcal{T}} u_i v_i$$

Constraints

The generated pattern must be valid

$$\sum_{i\in\mathcal{T}}u_iw_i <= W_S,$$

Non-negativity and integrality constraints

$$u_i \in \mathbb{Z}_+, \quad \forall i \in \mathcal{I}.$$

Column Generation

repeat

Start with a set of 'initial' patterns (m) and solve the master problem.

Find the multipliers corresponding to the demand constraints: get v_i .

Solve the subproblem (knapsack) and obtain a new cutting pattern.

until the subproblem has a negative objective value;



AMPL Modeling Tip 1: Master and subproblem

```
Master problem
var Cut {PATTERNS} integer >= 0;  # stocks cut using a pattern
minimize Number:
                                    # minimize total stock rolls
   sum {p in PATTERNS} Cut[p];
subject to Fill {i in ITEMS}:
   sum {p in PATTERNS} a[i,p] * Cut[p] >= demand[i];
Subproblem
var Use {ITEMS} integer >= 0;
minimize Reduced Cost:
   1 - sum {i in ITEMS} price[i] * Use[i];
subj to Width_Limit:
   sum {i in ITEMS} i * Use[i] <= W_S;</pre>
```

AMPL Modeling Tip 2: Run File

```
model csp.mod; data csp.dat;
problem Cutting_Opt: Cut, Number, Fill;
problem Pattern_Gen: Use, Reduced_Cost, Width_Limit;
repeat {
   solve Cutting_Opt;
   let {i in WIDTHS} price[i] := Fill[i].dual;
   solve Pattern_Gen;
   if Reduced_Cost < -0.00001 then {
      let nPAT := nPAT + 1;
      let {i in WIDTHS} nbr[i,nPAT] := Use[i];
      }
   else break;
   };
```

See csp.mod, csp.dat and colgen.ampl