

Integral Column Generation

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Overview

- 1 Introduction
- 2 Literature review
- 3 Integral simplex using decomposition
- 4 Integral column generation: a proof of concept
- 5 References
- 6 Conclusion

Introduction

Consider the set partitioning problem (\mathbb{P}):

$$(\mathbb{P}) \quad \min \sum_{j \in N} c_j x_j \quad (1)$$

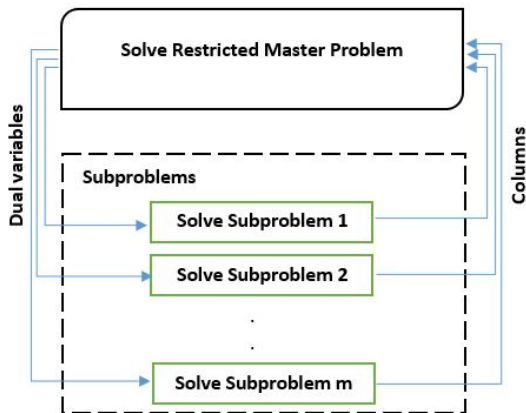
$$\text{s.t.:} \quad \sum_{j \in N} a_{ij} x_j = 1 \quad \forall i \in T \quad (2)$$

$$x_j \text{ binary} \quad \forall j \in N \quad (3)$$

- 1 T is a set of tasks (e.g. flights, bus trips, customers to visit), N is a set of columns (e.g. pilot/driver schedules), $A = (a_{i,j})$ is the constraint matrix with binary coefficients. **Let LP be the linear relaxation of \mathbb{P} .**
- 2 **Many applications in the industry:** vehicle and crew scheduling (air, rail, bus), data clustering, ...

Literature review: Branch-and-Price

- Branch-and-Price = Branch-and-Bound + Column Generation.



Many success stories since the late 80's: air, rail, bus industries...

Literature review: Branch-and-Price

- **Branch-and-Price** = Branch-and-Bound + **Column Generation**.

Advantages

- 1 Solve large programs (with special structure: part of the constraint matrix is diagonal by blocks).
- 2 Better lower bound.
- 3 Can handle nonlinearities in the subproblem.
- 4 Exact method.
- 5 ...

But, in the other hand ...

Literature review: Branch-and-Price

- **Branch-and-Price** = Branch-and-Bound + **Column Generation**.

Issues

- 1 Branch-and-price is a dual-fractional method (Letchford and Lodi (2002)).
- 2 The branching tree is huge in large reallife problems, integer solutions come too late!!!
- 3 Two many CG iterations because we consider at a given iteration only columns that are good for LP.
- 4 Plateau, yo-yo, tailing-off, heading-in, some headaches...

Some issues could be fixed ...

Literature review: Integral simplex

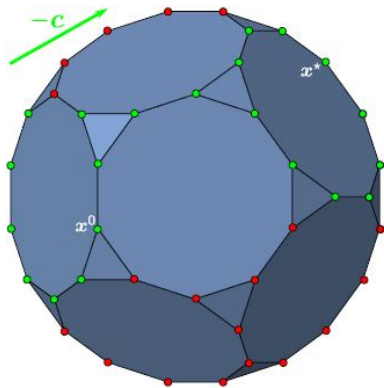


Figure : LP (Rosat et al., 2016).

- 1 Trubin (1969): quasi-integrality; i.e. every edge of $\text{Conv}(\mathbb{P})$ is an edge of LP.
 - 2 Balas and Padberg (1972,1975): existence of *an integral path* with decreasing cost leading to an optimal integer solution.
 - 3 Thompson (2002): Integral simplex method. Small instances solved : 163 constraints
 - 4 Saxena (2003): generalization of Thompson(2002) results...
- **The big issue: degeneracy.**

First integration with column generation

Rönning and Larsson (2009, 2014): all-integer column generation.

- All-integer pivots on columns and surrogate columns.
- Over generation.
- Optimality condition.
- Numerical results for generalized assignment problem (10 agents, 30 jobs).
- Still, the big issue is degeneracy.

Main points of view

- 1 **Avoid degeneracy:** increase the number of fractional variables; efficient against degeneracy but generally not good for branching.
- 2 **Profit from degeneracy:** to reduce the problem size and the number of fractional variables (basis reduced), by using for instance dynamic constraint/variable aggregation (Elhallaoui et al. (2005, 2010), Bouarab et al.(2014)).

In summary

- Solutions are either highly degenerate and "fractional" or nondegenerate and highly fractional!
- Let us get a look outside the box ...

Integral simplex using decomposition (ISUD): motivation

- Given a current integer solution \bar{x} , $S = \{j | \bar{x}_j \neq 0\}$.

Definition

A set $N' \subset N$ is **row-disjoint** if $A_{j_1} \cdot A_{j_2} = 0$, $\forall (j_1, j_2) \in N' \times N'$, $j_1 \neq j_2$.

Definition

A column or a (positive) combination of columns is said to be **compatible** if it is linearly dependent on columns indexed in S . Otherwise, it is said to be **incompatible**.

Theorem

*We move on to a next better adjacent integer solution **iff** the combination of columns we pivot on is a negative reduced cost, compatible, minimal, and composed of row-disjoint columns.*

Integral simplex using **decomposition** (ISUD)

- We can now use this notion of compatibility to **decompose** the problem:

$$A = \begin{array}{c} A_S \quad \begin{array}{|c|c|} \hline A_{C_S} & A_{I_S} \\ \hline \end{array} \\ \text{Compatible} \quad \text{Incompatible} \end{array}$$

Integral simplex using **decomposition** (ISUD)

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CompatibleIncompatible

↓

RP

$$\min_{x_{C_S}} \quad c_{C_S} \cdot x_{C_S} \quad (4)$$

$$\text{sc:} \quad A_{C_S} x_{C_S} = e \quad (5)$$

$$x_{C_S} \in \{0, 1\}^{|C_S|} \quad (6)$$

Integral simplex using **decomposition** (ISUD)

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$$A = \begin{array}{|c|c|c|} \hline A_S & A_{C_S} & A_{I_S} \\ \hline \end{array}$$

Compatible Incompatible

↓

CP

$$\text{reduced cost} \rightarrow \min_{v, \lambda} \sum_{j \in I_S} c_j v_j - \sum_{I \in S} c_I \lambda_I \quad (4)$$

$$\text{compatibility constraints} \rightarrow \text{st: } \sum_{j \in I_S} v_j A_j - \sum_{I \in S} \lambda_I A_I = 0 \quad (5)$$

$$\text{normalization constraint} \rightarrow \sum_{j \in I_S} w_j v_j = 1 \quad (6)$$

$$v \geq 0, \quad \lambda \in \mathbb{R}^{|S|} \quad (7)$$

Integral simplex using decomposition (ISUD): mechanics

Remark

- Positive (v_j) are entering variables, positive (λ_l) are leaving variables.
- The vector $d = ((v_j), -(\lambda_l), 0)$ is a descent direction if the reduced cost is negative.
- Constraint (5) could be replaced by $MAv = 0$. M is the **compatibility** matrix.
- So, CP becomes: $\min \bar{c} \cdot v, MAv = 0, \sum_{j \in I_S} w_j v_j = 1, v \geq 0$.

Proposition

- The combination $v_j > 0$ found by CP is compatible and *minimal* (*non-decomposable*).
- If \bar{x} is not optimal to \mathbb{P} , CP admits a row-disjoint minimal negative reduced cost combination as a solution.
- The new solution is “simply” obtained by exchanging the leaving variables (λ_l) with the entering ones (v_j) .

ISUD algorithm

- Step 0:** Start with an initial integer solution.
- Step 1: Improve** the current integer solution with efficient pivots in the reduced problem.
- Step 2: Improve** the current integer solution with a compatible combination of columns (v_j) found by the complementary problem (making some branching if necessary).
- Control:** If Step 2 improves the solution, go to Step 1. Otherwise, the current solution is optimal.

Advantages

- 1 Primal exact approach.
- 2 CP finds frequently and rapidly row-disjoint solutions without suffering from degeneracy.
- 3 Faster than CPLEX on some hard instances.
- 4 Seed for other projects:
 - Primal cuts, normalization (Rosat *et al.* 2014, 2016);
 - Zooming approach, new formulation of CP (Zaghroui *et al.* 2014, 2016);
 - Parallelization (Foutlane *et al.*, under progress), and
 - **Integral column generation.**

Some practical observations

- ① We can obtain in practice initial starting **green** points with good primal information.
 - Follow vehicles (aircraft, bus...), i.e. derive a starting point (crew schedules) from vehicle routes (easy to find in general).
 - Use the perturbed planning to derive a starting point in a reoptimization after perturbation.
 - Learn from historical data to get a starting point.
- ② Local improvement of an integer solution is also highly desirable in practice. It is possible in practice to define area with potential improvement around the current **green** point by "accurately" measuring incompatibility.

Integral column generation: ISUD + Column generation

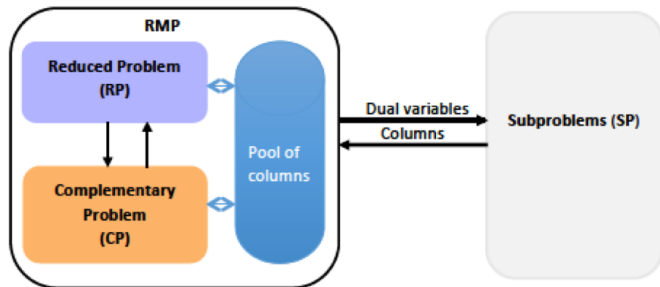


Figure : ICG¹: Solving RMP by ISUD.

Proposition

There exists at least one vector of dual values $\alpha \in \mathbb{R}^m$ ("corresponding" to the current integer solution; could be derived from CP solution) such that all entering variables (in a descent direction) have a negative reduced cost.

Proposition

Let S^* be the index set of variables taking 1 in an optimal integer solution. There exists at least one dual vector ("corresponding" to the current integer solution) such that all variables indexed in $S^* \setminus S$ have a non-positive reduced cost.

Integral column generation: implementation

Some tips

- Generate **interesting**, from integrality point of view, columns as much as you can and handle them in a pool.
- Solve the restricted master problem with ISUD:
 - Use a multiphase strategy: consider at phase k columns j with $\|MA_j\|_1 \leq k$; increase k as needed.
- Loop until satisfaction.

Remark

- In phase k , the number of nonzero elements in any column of CP does not exceed $k + 1$.

Integral column generation: numerical results

Tasks	Diving B&P				ICG^1			
	Itr	Col	Obj	Time(s)	Itr	Col	Obj	Time(s)
240	43	7744	60	0,6	3	22907	60	1
320	79	17614	477	2	4	24516	477	2
400	62	21069	60	4	3	101180	60	8
480	89	34748	477	7	5	78381	477	11
640	66	37236	477	14	7	173976	477	27
720	151	86648	747	45	5	137382	747	34
800	144	107707	447	47	4	260769	447	57

Table : ICG^1 vs. B&P (small instances)

Diving B&P is slightly better on these small instances. However, the number of iterations is drastically reduced!

Integral column generation: numerical results






Tasks	Diving B&P				ICG^1			
	Itr	Cols	Obj	Time (s)	Itr	Cols	Obj	Time (s)
960	294	150072	1378	115	5	143011	1378	42
1200	238	173895	173895	182	6	213042	1849	67
1200	249	317804	747	311	5	461902	747	159
1600	270	404115	880	689	6	568539	880	278
2000	359	705557	1259	3150	5	874990	1259	578

Table : ICG^1 vs. B&P (medium & large instances)





ICG is better on larger instances. Average reduction factors are:

- Time: 3
- Iterations: 85

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Conclusion

- Seems **working** good but needs some extensive testing and tuning.
- Could be **generalized** to SPP with side constraints. May be to general binary programs!
- Characterize fractional solutions better to **penalize** them in the normalization constraint!!

Thanks for your attention!