Solving a Challenging Quadratic 3D Assignment Problem

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quadratic objective

 $c_{ijkpqr} x_{ijk} x_{pqr}$



 $C_{ij}kpqr$

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16-PSK digital communication retransmission protocol

 c_{ijkpqr}

 cost of assigning to strings i and p the symbols j and q in the first transmission and k and r in the second

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- extremely dense objective: >12M coefficients
- high dynamism 3.6×10^{12}
- symmetric: group of order 49.152

Parallel mode: deterministic, using up to 16 threads. Root relaxation solution time = 43.45 sec. (17943.71 ticks)

Nodes					Cuts/						
No	de	Left	Objective	IInf	Best]	Integer	Best	Bound	ItCn	t	Gap
*	0+	0			20739	92.0000		0.0000	453	8 100	.00%
	0	0	9832.0000	50	20739	92.0000	983	2.0000	453	8 95	.26%
	0	0	9832.0000	50	20739	92.0000	Cu	ts: 12	545	0 95	.26%
	0	0	9832.0000	55	20739	92.0000	Cu	ts: 25	556	9 95	.26%
Heuri	stic	still l	ookina.								
	0	2	9832.0000	51	20739	92.0000	983	2.0000	556	9 95	.26%
Elaps	ed t	ime = 18	86.17 sec. (166732	.53 tic	cks.tr	ee = 0.0	1 MB.	solution	s = 1)	
•	1	3	10639.0000	39	20739	92.0000	983	2.0000	1152	9 95	.26%
•••											
•••											
•••											
2595	3439	2548164	7 16202.	0920	34	207392	.0000	11819	.7613 3.	89e+08	94.30%
2595	8606	2548674	l0 cu	toff		207392	.0000	11819	.8664 3.	89e+08	94.30%
2596	5184	2549318	81 27448.	9838	33	207392	.0000	11820	.0129 3.	89e+08	94.30%
2597	3355	2550128	21883.	6636	33	207392	.0000	11820	.0279 3.	89e+08	94.30%
Elaps	ed t	ime = 18	88682.61 sec	. (701	11125.7	75 tick	s. tree	= 8573	3.89 MB.	solut	ions = 1)
Nodef	ile	size = 8	35605.64 MB	(8364.	42 MB c	after co	ompressi	on)	,		
2598	2488	2551019	23406.	9047	37	207392	.0000	11820	.2149 3.	89e+08	94.30%
2599	2703	2552026	52 111140.	2318	24	207392	.0000	11820	.4710 3.	89e+08	94.30%
2600	4478	2553183	24797.	8353	29	207392	.0000	11820	.5560 3.	89e+08	94.30%
2601	3616	2554084	3 114000.	7561	32	207392	.0000	11820	.8606 3.	89e+08	94.30%
2602	1413	2554847	25846.	1198	35	207392	.0000	11821	.0349 3.	90e+08	94.30%
2602	3631	2555065	51 cu	toff		207392	.0000	11821	.0669 3.	90e+08	94.30%

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I. lightweight MIP model

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2. cutting planes

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3. symmetry handling

How did we solve it?

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} w_{ijk}$$

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$$w_{ijk} \ge \sum_{p=1}^{n} \sum_{q=1}^{n} \sum_{r=1}^{n} c_{ijkpqr} x_{pqr} - M(1 - x_{ijk})$$

$$x_{ijk} \in \{0, 1\}$$

$$w_{ijk} \ge 0$$

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variables and

constraints

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- NP-hard in theory, quite cheap in practice
- can exploit additional constraints (if available)
 both global and local

$$L_{ijk} = \begin{cases} Cutting Planes I \\ \min \sum_{p=1}^{n} \sum_{q=1}^{n} \sum_{r=1}^{n} c_{ijkpqr} x_{pqr} \\ \sum_{p=1}^{n} \sum_{q=1}^{n} x_{pqr} = 1 \quad \forall r \in \{1, \dots, n\} \\ \sum_{p=1}^{n} \sum_{r=1}^{n} x_{pqr} = 1 \quad \forall q \in \{1, \dots, n\} \\ \sum_{q=1}^{n} \sum_{r=1}^{n} x_{pqr} = 1 \quad \forall p \in \{1, \dots, n\} \\ x_{ijk} = 1 \\ x_{pqr} \in \{0, 1\} \end{cases}$$

$w_{ijk} + w_{pqr} \ge T_{ijkpqr}(x_{ijk} + x_{pqr} - 1)$

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computed by solving a MIP

- increase consistency between pairs of artificial variables
- not significantly harder than family I
- need to be conservative with separation

$$\min \quad w_{ijk} + w_{pqr}$$

$$\sum_{s=1}^{n} \sum_{t=1}^{n} x_{pqr} = 1 \quad \forall u \in \{1, \dots, n\}$$

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$$\sum_{t=1}^{n} \sum_{u=1}^{n} x_{pqr} = 1 \quad \forall s \in \{1, \dots, n\}$$

$$w_{ijk} \ge \sum_{s=1}^{n} \sum_{t=1}^{n} \sum_{u=1}^{n} c_{ijkstu} x_{stu}$$

$$w_{pqr} \ge \sum_{s=1}^{n} \sum_{t=1}^{n} \sum_{u=1}^{n} c_{pqrstu} x_{stu}$$

$$x_{ijk} = 1$$

$$x_{pqr} = 1$$

$$x_{stu} \in \{0, 1\}$$

 $T_{ijkpqr} =$

Symmetry Handling

binary variables can be partitioned into 6 orbits


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sums within orbits stay the same

binary variables can be partitioned into 6 orbits



sums within orbits stay the same aggregated variables as first level decisions

symmetry decomposition based on orbital shrinking

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isomorphism pruning within sub-MIPs... exploit symmetry twice!!!

Aggregated Model

$$\begin{cases} y_0 + y_1 + y_2 + y_3 + y_4 + y_5 = 16 \\ y_1 + 2y_3 + y_4 = 16 \\ y_2 + y_4 + 2y_5 = 8 \\ 2y_0 + y_1 + y_2 = 8 \\ y_i \in \{0, \dots, |O_i| - 1\} \quad \forall i \in \{0, \dots, 5\} \end{cases}$$

6 orbits \mapsto 6 y variables

Nice Interplay between techniques

symmetry decomposition

MIP model

cutting planes

Is it enough?

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0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 0 1 2 3 4 6 5 7 8 10 9 11 12 13 14 15 6 14 2 10 8 12 0 4 11 15 3 7 5 13 1 9

Rank variables by decreasing values of Lijk

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- Improves dual bound fast (higher priority variables are the most expensive ones)

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- Improves dual bound fast (higher priority variables are the most expensive ones)
- Plays well with isomorphism pruning

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- cuts are added only if at least 10 are significantly violated
- expensive cuts are separated only if one of the two controlling variables is already fixed to 1
- used indicator constraints to speed up LPs

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- resulting LP objective values (multiplied by the same factor) are still valid dual bounds
- primal solutions are evaluated with the exact coefficients

subproblems	count	time	nodes
easy	45	2,800	950

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less than one week on a desktop PC!

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 developed (extended) techniques that can be used for other Q3APs and (more importantly) QAPs and beyond...

Selected Literature

- Pierskalla: The multi-dimensional assignment problem. Operations Research 16, 422–431 (1968)
- Hahn, Kim, Stützle, Kanthak, Hightower, Samra, Ding, Guignard: The quadratic three-dimensional assignment problem: Exact and approximate solution methods. EJOR 184, 416–428 (2008)
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- Wu, Mittelmann, Wang, Wang: On computation of performance bounds of optimal index assignment. IEEE Transactions on Communications 59, 3229–3233 (2011)
- Margot: Symmetry in Integer Linear Programming. 50 Years of Integer Programming 1958-2008, 647–686 (2010)

Thanks for your attention!

Questions?