Two Clause Learning Approaches for Disjunctive Scheduling

Mohamed Siala, Christian Artigues, and Emmanuel Hebrard



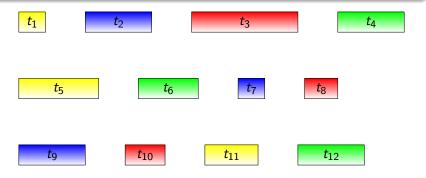




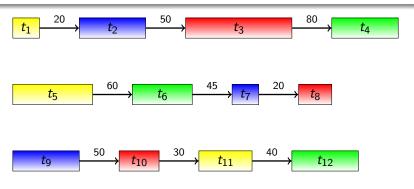


Disjunctive Scheduling

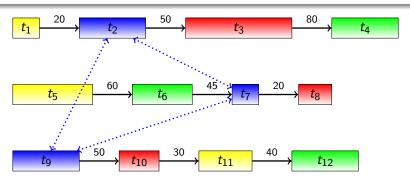
Disjunctive Scheduling



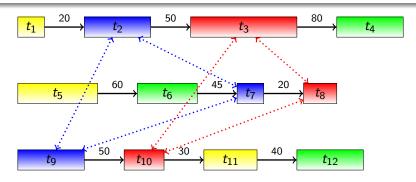
Disjunctive Scheduling



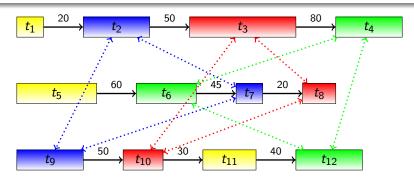
Disjunctive Scheduling



Disjunctive Scheduling

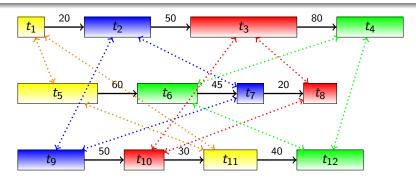


Disjunctive Scheduling



Disjunctive Scheduling

A family of scheduling problems having in common the Unary Resource Constraint.



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Scheduling in CP

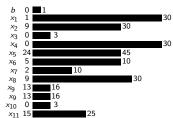
- Tradition
 - Tailored propagation algorithms (such as Edge-Finding [Carlier and Pinson, 1989]
 - Tailored search strategies (such as Texture [Sadeh, 1991]).

Scheduling in CP

- Tradition
 - Tailored propagation algorithms (such as Edge-Finding [Carlier and Pinson, 1989]
 - Tailored search strategies (such as Texture [Sadeh, 1991]).
- New trend: Focus on what can be learnt during search
 - Lazy Clause Generation for RCPSP [Schutt et al., 2013].
 - Weight-based heuristic learning on disjunctive scheduling [Grimes and Hebrard, 2015].

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```
\begin{array}{l} x_1 + x_7 \geq 4 \land \\ x_2 + x_{10} \geq 11 \land \\ x_3 + x_9 = 16 \land \\ x_5 \geq x_8 + x_9 \land \\ b \leftrightarrow (x_9 - x_4 = 14) \land \\ b \rightarrow (x_6 \geq 7) \land \\ b \rightarrow (x_6 + x_7 \leq 9) \land \\ x_{11} \geq x_9 + x_{10} \end{array}
```



 $\begin{array}{l} x_1+x_7 \geq 4 \wedge \\ x_2+x_{10} \geq 11 \wedge \end{array}$

 x_{11} 15

Example

$$[x_1 = 1]$$



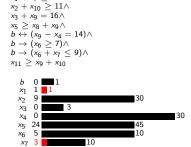
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 $x_1 + x_7 \ge 4 \land$

x₈ 9 x₉ 13 16 x₉ 13 16 x₁₀ 0 3 x₁₁ 15

Example

$$\llbracket x_1 = 1 \rrbracket \longrightarrow \llbracket x_7 \ge 3 \rrbracket$$



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 $x_1 + x_7 \ge 4 \land$

x₈ 9 x₉ 13 16 x₉ 13 16 x₁₀ 0 3 x₁₁ 15

Example

$$[x_1 = 1] \longrightarrow [x_7 \ge 3]$$

$$[x_2 = 9]$$



 $x_1 + x_7 \ge 4 \land$

x₈ 9 x₉ 13 16 x₉ 13 16 x₁₀ 2 3 x₁₁ 15

Example

$$\llbracket x_1 = 1 \rrbracket \longrightarrow \llbracket x_7 \ge 3 \rrbracket$$

$$[x_2 = 9] \longrightarrow [x_{10} \ge 2]$$



$$\llbracket x_1 = 1 \rrbracket \longrightarrow \llbracket x_7 \ge 3 \rrbracket$$

$$\llbracket x_2 = 9 \rrbracket \longrightarrow \llbracket x_{10} \ge 2 \rrbracket$$

$$[x_3 = 2]$$



 x_9 13 16 16 x_9 13 16 x_{10} 2 3 x_{11} 15

x₈ 9 x₉ 14 14 x₉ 13 16 x₁₀ 2 3 x₁₁ 15

Example

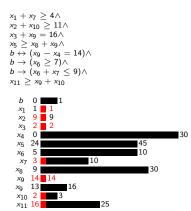
$$\llbracket x_1 = 1 \rrbracket \longrightarrow \llbracket x_7 \ge 3 \rrbracket$$

$$[x_2 = 9] \longrightarrow [x_{10} \ge 2]$$

$$[x_3 = 2] \longrightarrow [x_9 = 14]$$



$$[x_1 = 1]$$
 \longrightarrow $[x_7 \ge 3]$ $[x_2 = 9]$ \longrightarrow $[x_{10} \ge 2]$ $[x_3 = 2]$ \longrightarrow $[x_9 = 14]$ \longrightarrow $[x_{11} \ge 16]$



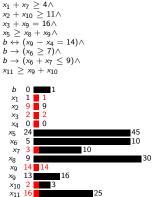
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$$\llbracket x_1 = 1 \rrbracket \longrightarrow \llbracket x_7 > 3 \rrbracket$$

$$\llbracket x_2 = 9 \rrbracket \longrightarrow \llbracket x_{10} \ge 2 \rrbracket$$

$$\llbracket x_3 = 2 \rrbracket \longrightarrow \llbracket x_9 = 14 \rrbracket \rightarrow \llbracket x_{11} \ge 16 \rrbracket$$

$$[x_4 = 0]$$

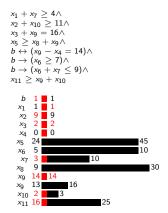


$$\begin{bmatrix} x_1 = 1 \end{bmatrix} \longrightarrow \begin{bmatrix} x_7 \ge 3 \end{bmatrix}$$

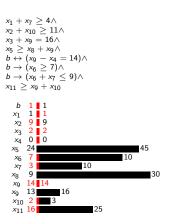
$$\begin{bmatrix} x_2 = 9 \end{bmatrix} \longrightarrow \begin{bmatrix} x_{10} \ge 2 \end{bmatrix}$$

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$$\begin{bmatrix} x_4 = 0 \end{bmatrix} \longrightarrow \begin{bmatrix} b = 1 \end{bmatrix}$$

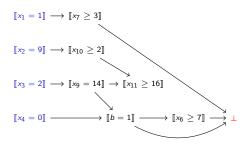


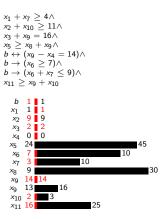
$$\begin{split} & \llbracket x_1 = 1 \rrbracket \longrightarrow \llbracket x_7 \geq 3 \rrbracket \\ & \llbracket x_2 = 9 \rrbracket \longrightarrow \llbracket x_{10} \geq 2 \rrbracket \\ & \llbracket x_3 = 2 \rrbracket \longrightarrow \llbracket x_9 = 14 \rrbracket \longrightarrow \llbracket x_{11} \geq 16 \rrbracket \\ & \llbracket x_4 = 0 \rrbracket \longrightarrow \llbracket b = 1 \rrbracket \longrightarrow \llbracket x_6 \geq 7 \rrbracket \end{split}$$



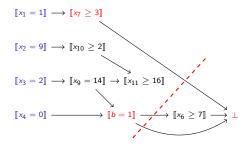
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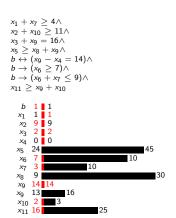




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 $\bullet \ \ \mathsf{Conflict} \ \ \mathsf{analysis:} \ \ \llbracket b=1 \rrbracket \land \llbracket x_7 \geq 3 \rrbracket \Rightarrow \bot$

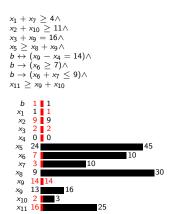


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$$\begin{bmatrix} x_1 = 1 \end{bmatrix} \longrightarrow [x_7 \ge 3] \\
 [x_2 = 9] \longrightarrow [x_{10} \ge 2] \\
 [x_3 = 2] \longrightarrow [x_9 = 14] \longrightarrow [x_{11} \ge 16] \\
 [x_4 = 0] \longrightarrow [b = 1] \longrightarrow [x_6 \ge 7] \longrightarrow \bot$$

- Conflict analysis: $\llbracket b=1 \rrbracket \land \llbracket x_7 \geq 3 \rrbracket \Rightarrow \bot$
- New clause: $\llbracket b \neq 0 \rrbracket \lor \llbracket x_7 \leq 2 \rrbracket$



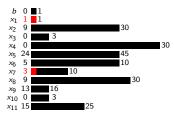
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$$[x_1 = 1] \longrightarrow [x_7 \ge 3]$$

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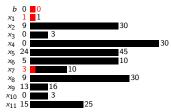




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- Propagate the learnt clause

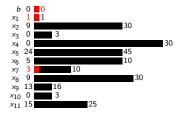




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- Backtrack to level 1
- Propagate the learnt clause
- Continue exploration





Learning in CP

- Hybrid CP/SAT
- Conflict Driven Clause Learning (CDCL) [Moskewicz et al., 2001]
- Based on the notion of explanation
- Forward/Backward explanations
- Domain atoms can be generated Eagerly/Lazily

Our contributions

- Alternative lazy (atom) generation approach
- Novel conflict analysis scheme tailored to disjunctive scheduling

Unary Resource Constraint

- $O(n^2)$ Boolean variables δ_{kij} $(i < j \in [1, n])$ per machine M_k .
- \bullet Decomposition using the following $\operatorname{Disjunctive}$ constraints:

$$\delta_{kij} = \begin{cases} 0 & \Leftrightarrow & t_{ik} + p_{ik} \le t_{jk} \\ 1 & \Leftrightarrow & t_{jk} + p_{jk} \le t_{ik} \end{cases}$$
 (1)



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- Branch on the Boolean variables of the DISJUNCTIVE constraints.
- Variable ordering: wdeg, VSIDS.
- Value ordering: Solution guided [Beck, 2007].
- Greedy heuristic, dichotomic search, branch and bound



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Revisiting Lazy Atom Generation



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Revisiting Lazy Atom Generation

Domain Encoding: standard approach

- **①** Generate domain atoms: $a \leftrightarrow [x = d]$, $b \leftrightarrow [x \le d]$
- ② Generate domain clauses: $\neg [x \le d] \lor [x \le d + 1]$, $\neg [x = d] \lor [x \le d]$, etc

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Revisiting Lazy Atom Generation

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Lazy Atom Generation

- Atoms and domain clauses are generated during conflict analysis
- There is a redundancy issue

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Revisiting Lazy Atom Generation

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Lazy Atom Generation

- Atoms and domain clauses are generated during conflict analysis
- There is a redundancy issue
- **③** Suppose that $[x \le 2]$, $[x \le 4]$ are already generated with $\neg [x \le 2] \lor [x \le 4]$ and we will generate $[x \le 3]$.
- **4** Add ¬[$x \le 2$] ∨ [$x \le 3$], ¬[$x \le 3$] ∨ [$x \le 4$].
- **6** For a domain of size k, k-2 redundant clauses.

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Key Idea

- Use a single constraint responsible for the consistency of the domain.
- Whenever an atom is generated, we update the internal structure of the constraint

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Definition

DomainFaithfulness $(x, [b_1 \dots b_n], [v_1, \dots, v_n]) : \forall i, b_i \leftrightarrow x \leq v_i$

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Definition

 ${\tt DomainFaithfulness}\big(x,[b_1\dots b_n],[v_1,\dots,v_n]\big): \forall i,b_i \leftrightarrow x \leq v_i$

Arc consistency

Can be enforced in constant amortized time complexity (O(1)) down a branch of the search tree

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- Branch on the reified Boolean variables
- \rightarrow There exists an explanation for every bound literal $[x \le u]$

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DISJUNCTIVE-based Learning

Two phases:

- 1-UIP cut
- Apply resolution for every bound literal until having a nogood with only reified Boolean variables

Example

• 1-UIP nogood: $a \land \neg b \land [x \le 7] \land [y \le 9] \Rightarrow \bot$

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Example

- 1-UIP nogood: $a \land \neg b \land [x \le 7] \land [y \le 9] \Rightarrow \bot$
- $\bullet \ \ c \land \llbracket z \leq 13 \rrbracket \Rightarrow \llbracket x \leq 7 \rrbracket$

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Example

- 1-UIP nogood: $a \land \neg b \land [x \le 7] \land [y \le 9] \Rightarrow \bot$
- $c \wedge [z \leq 13] \Rightarrow [x \leq 7]$
- Resolution $a \land \neg b \land c \land [z \le 13] \land [y \le 9] \Rightarrow \bot$

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Example

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- Resolution $a \land \neg b \land c \land \llbracket z \le 13 \rrbracket \land \llbracket x \ge 4 \rrbracket \Rightarrow \bot$

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Example

- 1-UIP nogood: $a \land \neg b \land [x \le 7] \land [y \le 9] \Rightarrow \bot$
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- Resolution $a \land \neg b \land c \land a \land [x \ge 0] \land [y \ge 4] \Rightarrow \bot$

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- Resolution $a \land \neg b \land c \land [z \le 13] \land [x \ge 4] \Rightarrow \bot$
- Resolution $a \land \neg b \land c \land a \land [x \ge 0] \land [y \ge 4] \Rightarrow \bot$
- Nogood Reduction $a \land \neg b \land c \land [y \ge 4] \Rightarrow \bot$

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Example

- 1-UIP nogood: $a \land \neg b \land [x < 7] \land [y < 9] \Rightarrow \bot$
- $c \wedge \lceil z < 13 \rceil \Rightarrow \lceil x < 7 \rceil$
- Resolution $a \land \neg b \land c \land [z < 13] \land [y < 9] \Rightarrow \bot$
- Resolution $a \land \neg b \land c \land [z \le 13] \land [x \ge 4] \Rightarrow \bot$
- $\bullet \quad a \land [x > 0] \Rightarrow [z < 13]$
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- Resolution $a \land \neg b \land c \land [z \le 13] \land [x \ge 4] \Rightarrow \bot$
- \bullet $a \land [x > 0] \Rightarrow [z < 13]$
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- Nogood Reduction $a \land \neg b \land c \land [y > 4] \Rightarrow \bot$
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Example

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- Resolution $a \land \neg b \land c \land \llbracket z \leq 13 \rrbracket \land \llbracket x \geq 4 \rrbracket \Rightarrow \bot$
- Resolution $a \land \neg b \land c \land a \land \llbracket x \ge 0 \rrbracket \land \llbracket y \ge 4 \rrbracket \Rightarrow \bot$
- Nogood Reduction $a \land \neg b \land c \land [y \ge 4] \Rightarrow \bot$
- Resolution $a \land \neg b \land c \Rightarrow \bot$
- No domain encoding
- Scheduling horizon does not manner in size
- ⊖ Language of literals is restricted compared to standard approaches

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Experimental results

Protocol

- **Mistral-Hybrid:** backward explanations, semantic reductions, lazy generation, DISJUNCTIVE-based learning
- http://siala.github.io/jssp/details.pdf
- Lawrence and Taillard Job Shop benchmarks
- Global cutoff: 1h

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How hard are Taillard instances?

- Proposed 2 decades ago
- State-of-the art method recently proposed in [Vilím et al., 2015]
 - IBM CP-Optimizer studio
 - 8h20min per instance
 - Parallelization
 - Start search with best known bounds as an additional information.

Instances	CP(t	ask)	H(ν	sids.	, disj)	H(vsids,	lazy)	H(t	ask,	disj)	H(i	task , I.	azy)	
					Most	ly pro	ven o	ptimal							
	%0 T	nds/s	%0	Т	nds/s	%0	Т	nds/s	%0	Т	nds/s	%0	Т	nds/s	
la-01-40	87 522	8750	91.5	437	6814	88	632	2332	90.50	434	5218	88.75	509	2694	
tai-01-10	89 768	5875	90	517	4975	88	1060	1033	90	634	3572	84	1227	1013	
	Hard instances														
	PRD nds/s PRD nds/s PRD nds/s PRD nds/s PRD nds/s PRD nds/s														
tai-11-20	1.8432	4908	1.15	64	3583	1.3	725	531	1.27	41	2544	1.2	824	489	
tai-21-30	1.6131	3244	0.91	.50	2361	1.0	841	438	0.96	60	1694	0.87	745	409	
tai-31-40	5.4149	3501	4.02	210	2623	3.	7350	580	4.05	36	1497	3.88	344	510	
tai-41-50	7.0439	2234	4.83	362	1615	4.6	008	436	4.93	05	1003	5.01	136	390	
tai-51-60	3.0346	1688	3.24	149	2726	3.7	'809	593	1.11	56	1099	1.16	575	575	
tai-61-70	6.8598	1432	6.58	390	2414	5.4	264	578	3.96	37	866	3.6	617	533	

Instances	CP(t	ask)	H(v	sids,	, disj)	H(vsids,	lazy)	H(t	ask,	disj)	H(i	task, l	azy)	
					Most	ly pro	ven o	ptimal							
	%0 T	nds/s	%0	Т	nds/s	%0	Т	nds/s	%0	Т	nds/s	%0	Т	nds/s	
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	PRD nds/s PRD PR														
tai-11-20	1.8432	4908	1.15	64	3583	1.3	725	531	1.27	41	2544	1.2	824	489	
tai-21-30	1.6131	3244	0.91	50	2361	1.0	841	438	0.96	60	1694	0.87	745	409	
tai-31-40	5.4149	3501	4.02	10	2623	3.	7350	580	4.05	36	1497	3.88	344	510	
tai-41-50	7.0439	2234	4.83	62	1615	4.6	008	436	4.93	05	1003	5.03	136	390	
tai-51-60	3.0346	1688	3.24	49	2726	3.7	'809	593	1.11	56	1099	1.16	575	575	
tai-61-70	6.8598	1432	6.58	90	2414	5.4	264	578	3.96	37	866	3.6	617	533	

• Hybrid models outperform CP

Instances	CP(t	ask)	H(vsic	ls , disj)	H(vsids,	lazy)	H(t	ask,	disj)	H(a	task , I	azy)		
				Most	ly pro	ven o	ptimal								
	%0 T	nds/s	%0	T nds/s	%0	Т	nds/s	%O	Т	nds/s	%0	Т	nds/s		
la-01-40	87 522	8750	91.5 43	7 6814	88	632	2332	90.50	434	5218	88.75	509	2694		
tai-01-10	89 768	5875	90 51	7 4975	88	1060	1033	90	634	3572	84	1227	1013		
	Hard instances														
	PRD														
tai-11-20	1.8432	4908	1.1564	3583	1.3	725	531	1.27	41	2544	1.2	824	489		
tai-21-30	1.6131	3244	0.9150	2361	1.0	841	438	0.96	60	1694	0.87	745	409		
tai-31-40	5.4149	3501	4.0210	2623	3.	7350	580	4.05	36	1497	3.88	344	510		
tai-41-50	7.0439	2234	4.8362	1615	4.6	008	436	4.93	05	1003	5.03	136	390		
tai-51-60	3.0346	1688	3.2449	2726	3.7	'809	593	1.11	56	1099	1.16	575	575		
tai-61-70	6.8598	1432	6.5890	2414	5.4	264	578	3.96	37	866	3.6	617	533		

• The impact of clause learning is more visible when the size of the instance grows

Instances	C	P(ta	sk)	H(v	/sids	, disj)	H(vsids,	lazy)	H(t	ask,	disj)	H(a	task , I.	azy)
						Most	ly pro	ven o	ptimal						
	% 0	Т	nds/s	%0	Т	nds/s	%O	Т	nds/s	%O	T	nds/s	% O	Т	nds/s
la-01-40	87	522	8750	91.5	437	6814	88	632	2332	90.50	434	5218	88.75	509	2694
tai-01-10															1013
	Hard instances														
	PRD nds/s PRD nds/s PRD nds/s PRD nds/s PRD nds/s														
tai-11-20	1.84	132	4908	1.15	64	3583	1.3	725	531	1.27	41	2544	1.2	824	489
tai-21-30	1.61	.31	3244	0.91	L50	2361	1.0	841	438	0.96	60	1694	0.87	745	409
tai-31-40	5.41	49	3501	4.02	210	2623	3.7	7350	580	4.05	36	1497	3.88	344	510
tai-41-50	7.04	139	2234	4.83	362	1615	4.6	800	436	4.93	05	1003	5.01	L36	390
tai-51-60	3.03	346	1688	3.24	149	2726	3.7	809	593	1.11	56	1099	1.16	575	575
tai-61-70	6.85	98	1432	6.58	390	2414	5.4	264	578	3.96	37	866	3.6	617	533

• DISJUNCTIVE-based learning outperforms the other models on medium sized instances

Instances	CP(t	ask)	H(v	sids,	disj)	H(vsids,	lazy)	H(t	ask,	disj)	H(task, lazy)			
					Most	ly pro	ven o	ptimal							
	%O T	nds/s	%0	Т	nds/s	%0	Т	nds/s	%0	Т	nds/s	%0	Т	nds/s	
la-01-40	87 522	8750	91.5	437	6814	88	632	2332	90.50	434	5218	88.75	509	2694	
tai-01-10	89 768	5875	90	517	4975	88	1060	1033	90	634	3572	84	1227	1013	
	Hard instances														
	PRD nds/s PRD nds/s PRD nds/s PRD nds/s PRD nds/s PRD nds/s														
tai-11-20	1.8432	4908	1.15	64	3583	1.3	725	531	1.27	41	2544	1.2	824	489	
tai-21-30	1.6131	3244	0.91	50	2361	1.0	841	438	0.96	60	1694	0.87	745	409	
tai-31-40	5.4149	3501	4.02	10	2623	3.	7350	580	4.05	36	1497	3.88	344	510	
tai-41-50	7.0439	2234	4.83	62	1615	4.6	800	436	4.93	05	1003	5.01	L36	390	
tai-51-60	3.0346	1688	3.24	49	2726	3.7	809	593	1.11	56	1099	1.16	575	575	
tai-61-70	6.8598	1432	6.58	90	2414	5.4	264	578	3.96	37	866	3.6	617	533	

• wdeg is the best choice with the largest instances.

Instances	CP(ta	ask)	H(v	/sids	, disj)	H(vsids,	lazy)	H(t	ask,	disj)	H(a	task , I.	azy)	
					Most	ly pro	ven o	ptimal							
	%0 T	nds/s	%0	Т	nds/s	%O	Т	nds/s	%0	Т	nds/s	%0	Т	nds/s	
la-01-40	87 522	8750	91.5	437	6814	88	632	2332	90.50	434	5218	88.75	509	2694	
tai-01-10	89 768	5875	90	517	4975	88	1060	1033	90	634	3572	84	1227	1013	
	Hard instances														
	PRD nds/s PRD nds/s PRD nds/s PRD nds/s PRD nds/s PRD nds/s														
tai-11-20	1.8432	4908	1.15	64	3583	1.3	725	531	1.27	41	2544	1.2	824	489	
tai-21-30	1.6131	3244	0.91	L50	2361	1.0	841	438	0.96	60	1694	0.87	745	409	
tai-31-40	5.4149	3501	4.02	210	2623	3.	7350	580	4.05	36	1497	3.88	344	510	
tai-41-50	7.0439	2234	4.83	362	1615	4.6	008	436	4.93	05	1003	5.01	L36	390	
tai-51-60	3.0346	1688	3.24	149	2726	3.7	'809	593	1.11	56	1099	1.16	575	575	
tai-61-70	6.8598	1432	6.58	390	2414	5.4	264	578	3.96	37	866	3.6	617	533	

• Surprisingly DISJUNCTIVE-based learns shorter clauses

Open instances from Taillard benchmark before [Vilím et al., 2015]

• 7 new bounds found with DISJUNCTIVE-based learning and VSIDS

tai	i13	tai	21	tai23		tai	25	tai	26	tai	29	tai	30
new	old	new	old	new	old	new	old	new	old	new	old	new	old
1305	1282	1613	1573	1514	1474	1544	1518	1561	1558	1576	1525	1515	1485

Open instances from Taillard benchmark before [Vilím et al., 2015]

 \bullet 7 new bounds found with $\operatorname{DISJUNCTIVE}\textsc{-}\textsc{based}$ learning and VSIDS

tai	13	tai	21	tai23		tai	25	tai	26	tai	29	tai	30
new	old	new	old	new	old	new	old	new	old	new	old	new	old
1305	1282	1613	1573	1514	1474	1544	1518	1561	1558	1576	1525	1515	1485
13	42	1642 1518		18	15	558	15	591	15	573	15	19	

- 8h20min per instance
- Parallelization
- Start search with best known bounds as an additional information.

Open instances from Taillard benchmark before [Vilím et al., 2015]

7 new bounds found with DISJUNCTIVE-based learning and VSIDS

tai	13	tai	21	tai	23	tai	i25	tai	26	tai	29	tai	30
new	old												
1305	1282	1613	1573	1514	1474	1544	1518	1561	1558	1576	1525	1515	1485
13	42	1642		1518		1558		1591		1573		15	19

- 8h20min per instance
- Parallelization
- Start search with best known bounds as an additional information.

Relaunch with 2h

- tai-29: 1583 (1573 in [Vilím et al., 2015])
- tai-30: 1528 (1519 in [Vilím et al., 2015])

Summary

- Alternative lazy (atom) generation approach avoiding a redundancy issue
- Novel conflict analysis mechanism
- Efficient in practice, specially for finding proofs

Future Research

- Applications to other scheduling problems?
- Learning with global constraints?
- Hand-crafted learning?

Thank you.

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