

Learning Precedences for Scheduling Problems with Graph Neural Networks

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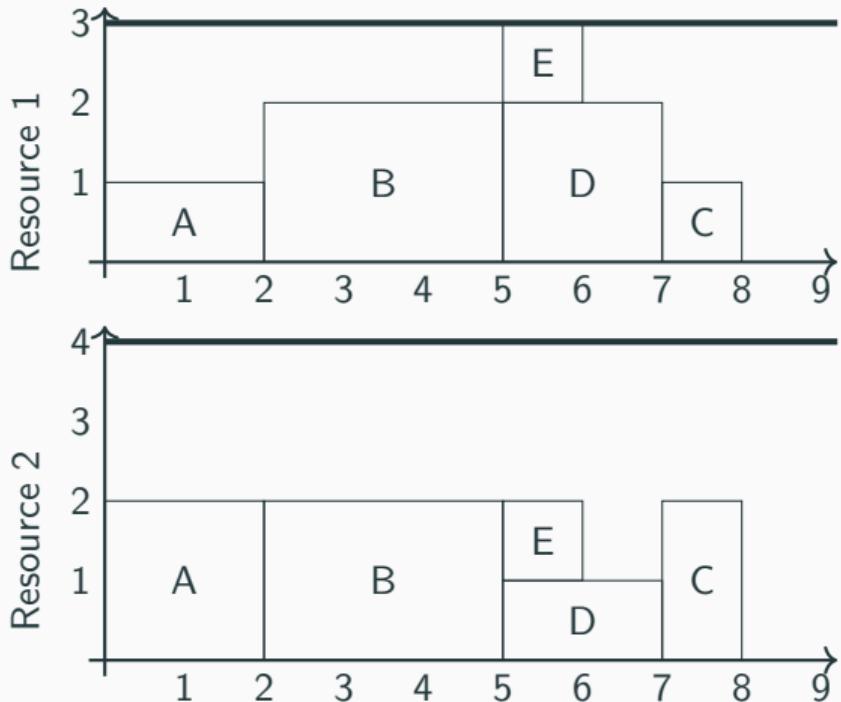
³ Université Laval, Quebec, Canada



Resource-Constrained Project Scheduling Problem (RCPSP)

Task	p_i	c_{ir_1}	c_{ir_2}	succ
A	2	1	2	B C D
B	3	2	2	E
C	1	1	2	
D	2	2	1	C
E	1	1	1	C

$C_{r_1} = 3$ and $C_{r_2} = 4$



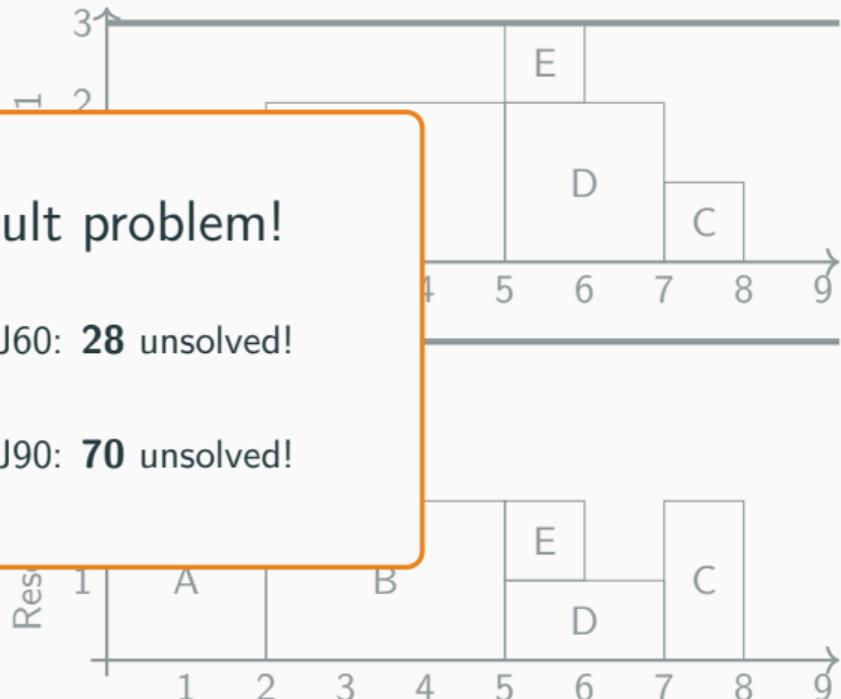
Task	p_i	c_{ir_1}	c_{ir_2}
A	2	1	2
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C	1	1	2
D	2	2	1
E	1	1	1

$$C_{r_1} = 3 \text{ and } C_{r_2} = 4$$

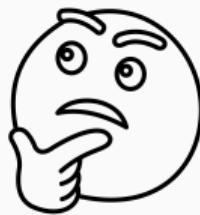
Difficult problem!

PSPlib J60: **28** unsolved!

PSPlib J90: **70** unsolved!



What if we had more information about the solution?

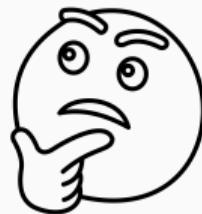


What if we had more information about the solution?



- Guide toward solution
- Reduce search space

How do I get more information about the solution?



How do I get more information about the solution?



How about Machine Learning?
Can we learn to predict
information?

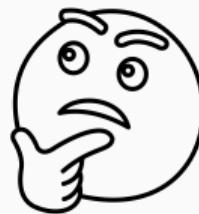
How do I get more information about the solution?



How about Machine Learning?
Can we learn to predict
information?

Which ML tool?

Which information could be useful?



Which information could be useful?

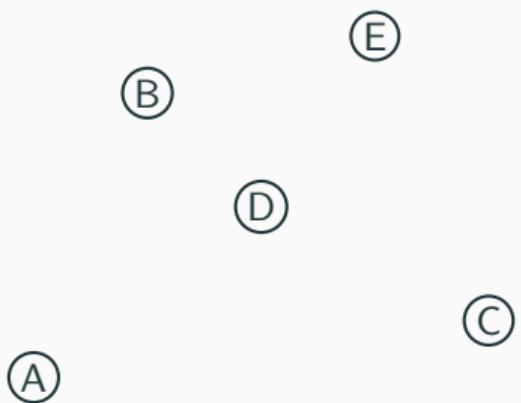


Precedences between pairs of tasks

RCPSP as a graph: the precedence graph

Task	p_i	c_{ir_1}	c_{ir_2}	succ
A	2	1	2	B C D
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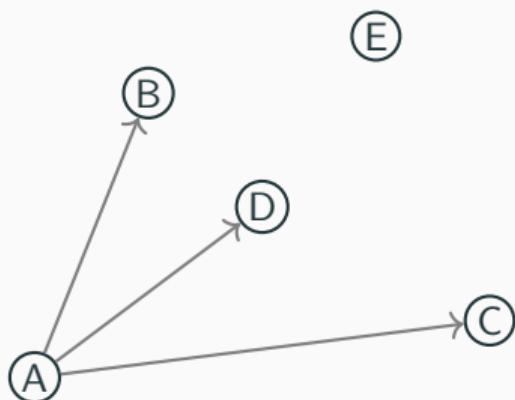
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RCPSP as a graph: the precedence graph

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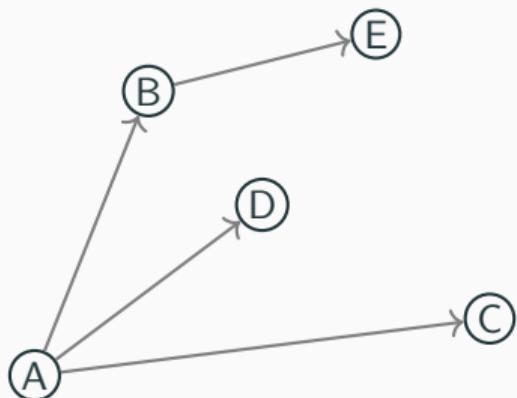
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RCPSP as a graph: the precedence graph

Task	p_i	c_{ir_1}	c_{ir_2}	SUCC
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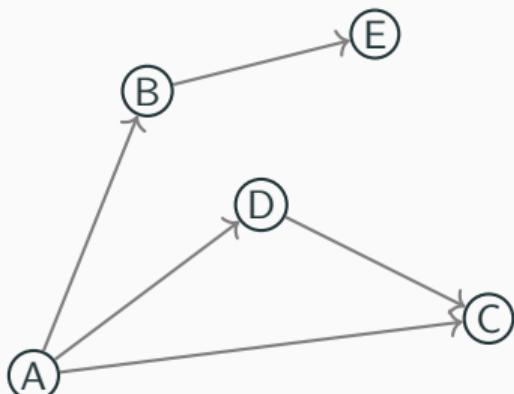
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RCPSP as a graph: the precedence graph

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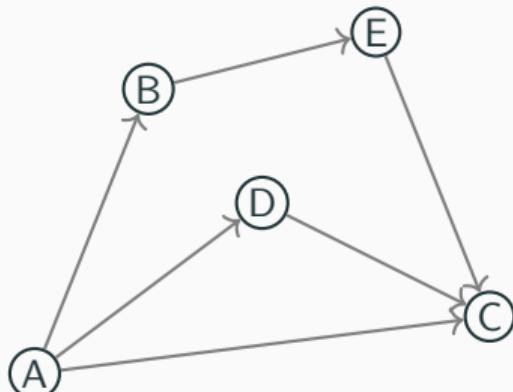
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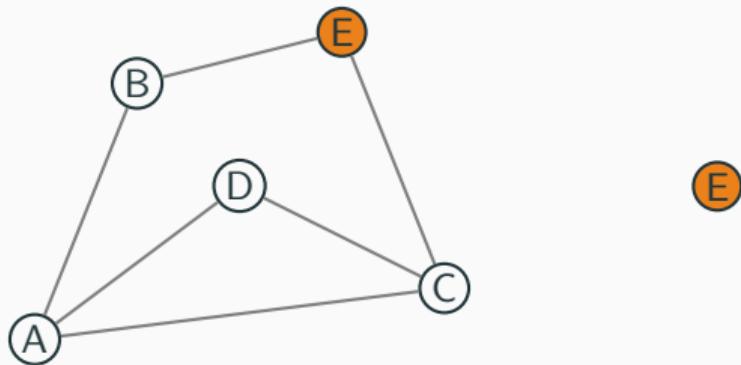
RCPSP as a graph: the precedence graph

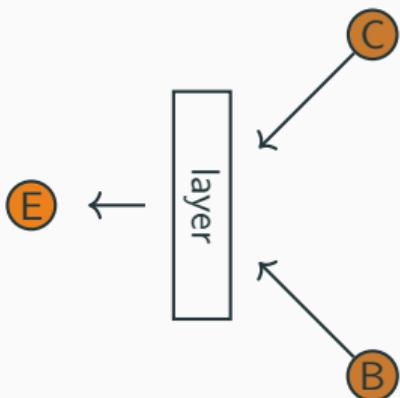
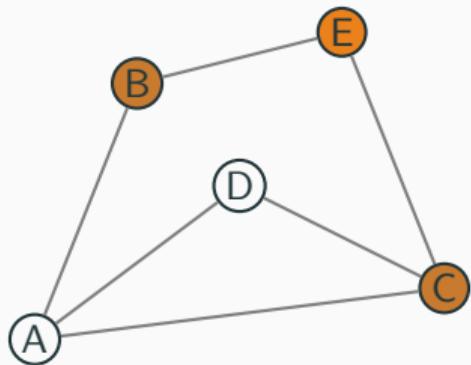
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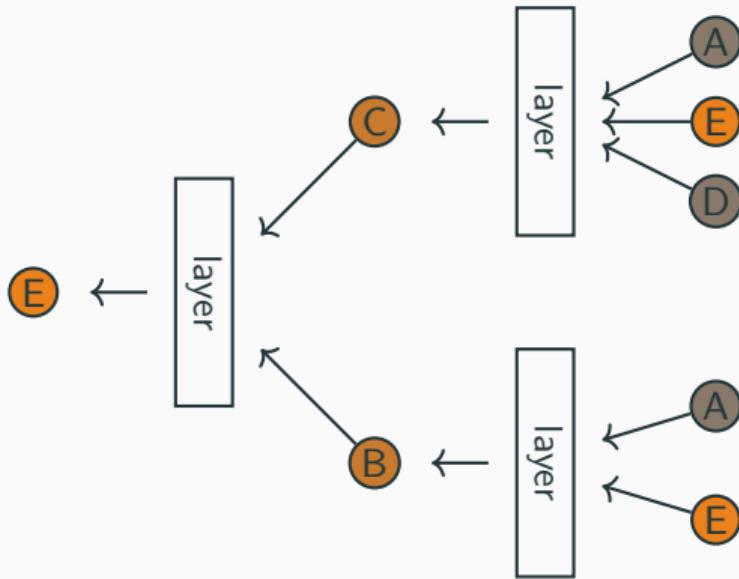
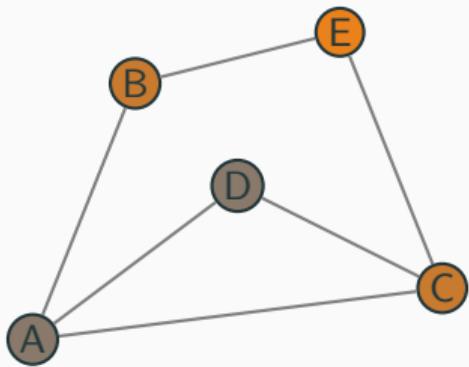
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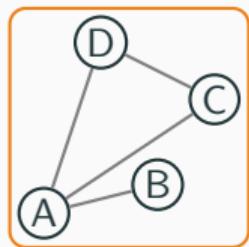


Graph Neural Networks



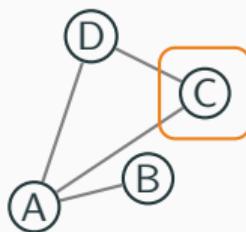






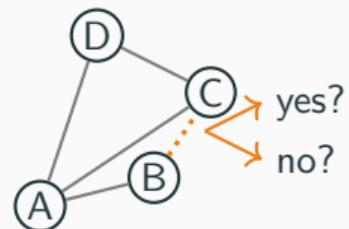
class A?
class B?

Graph classification



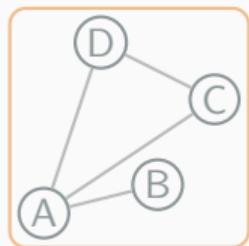
class A?
class B?

Node classification



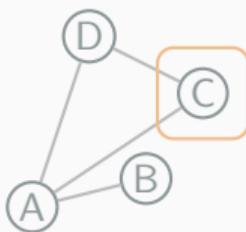
yes?
no?

Link prediction



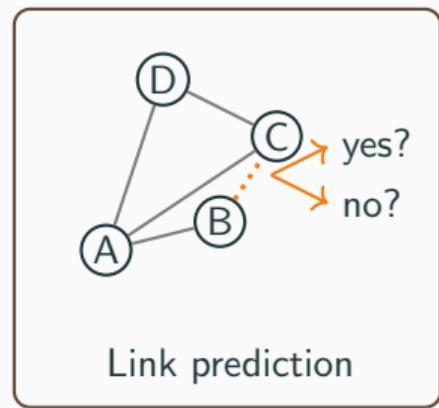
Graph classification

class A?
class B?



Node classification

class A?
class B?

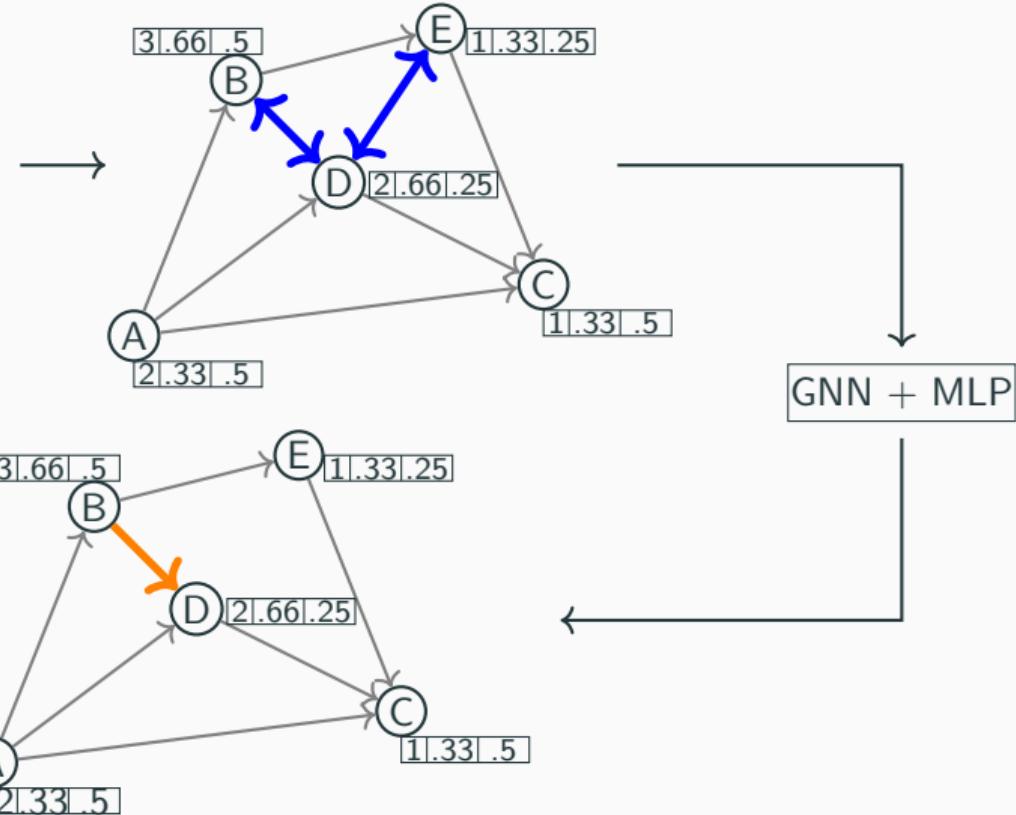


Link prediction

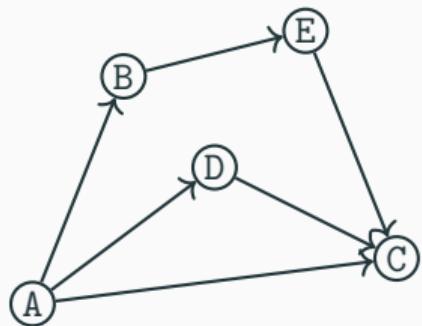
Methodology

Our method

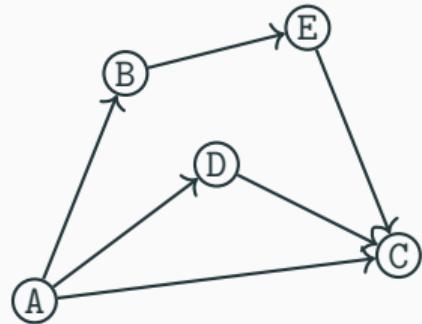
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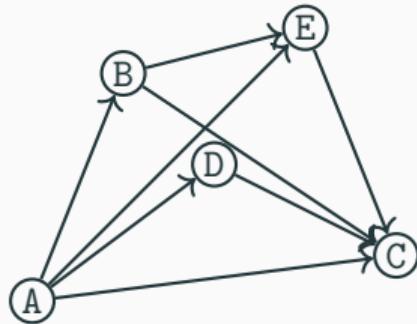
Instance



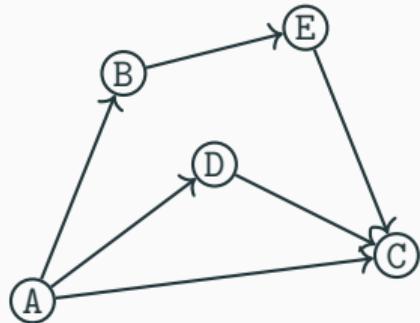
Instance



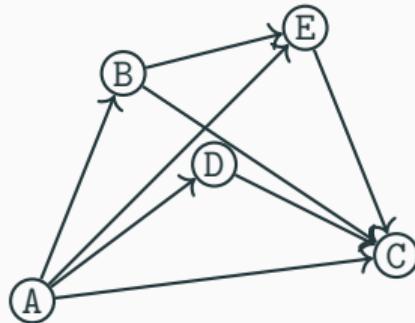
Transitive closure



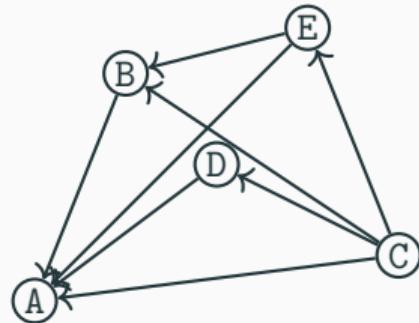
Instance



Transitive closure

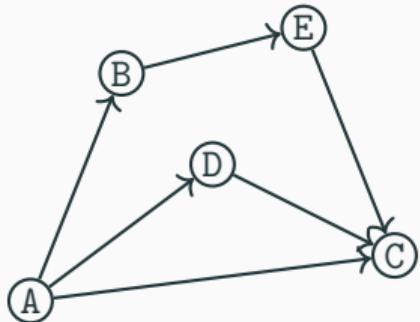


Avoided

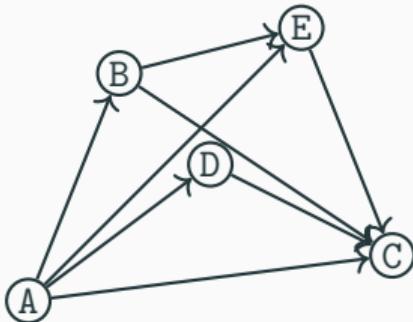


Candidate edge

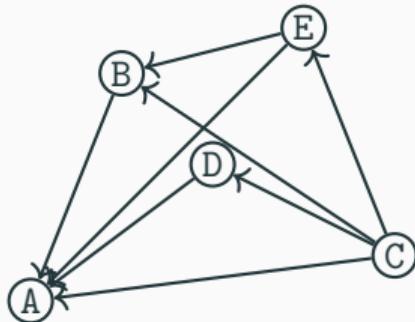
Instance



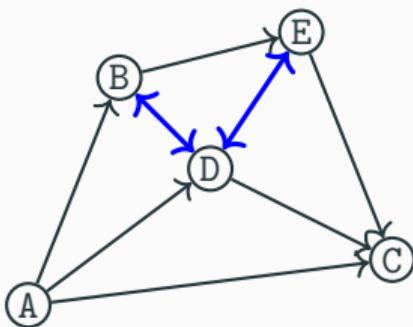
Transitive closure

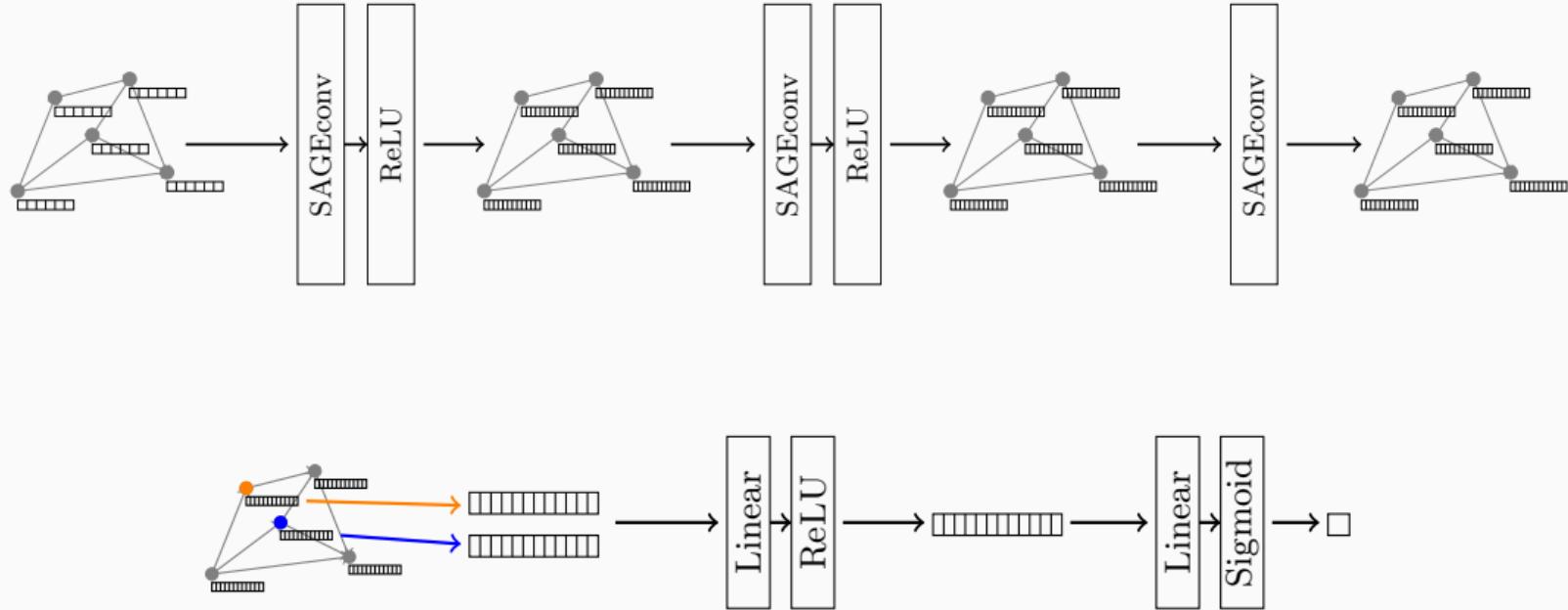


Avoided



Candidate





Additional precedences

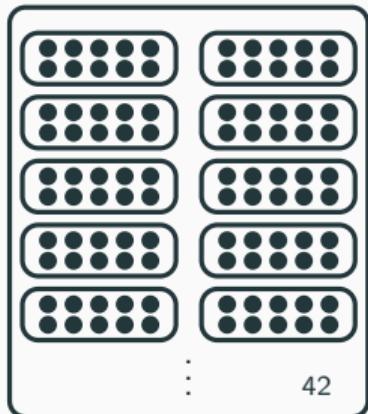
- + reduces search space
- restriction of the problem

Ordering heuristic

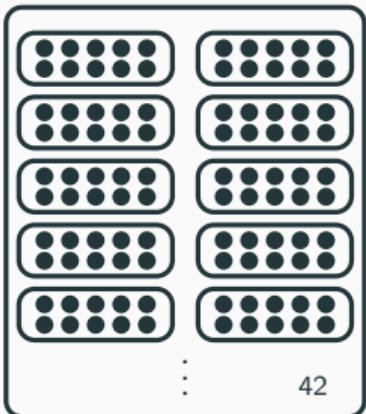
- + preserve solutions
- static ordering are slower

Results

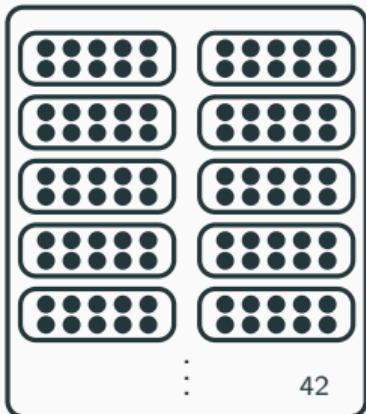
J30



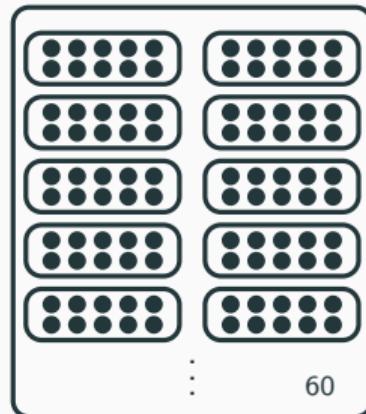
J60



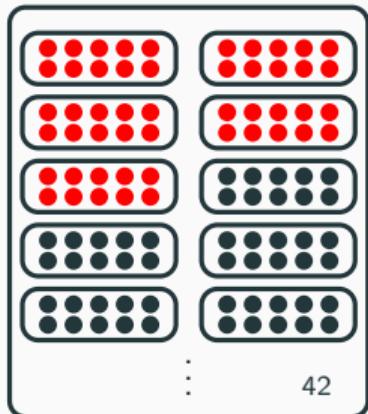
J90



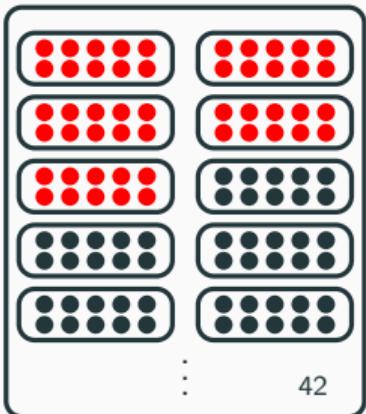
J120



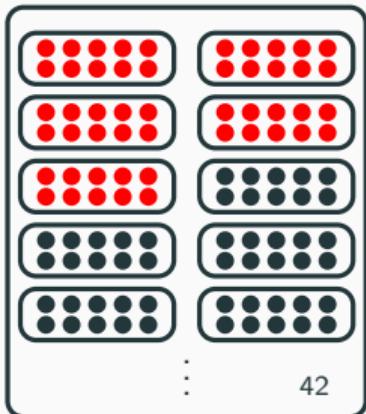
J30



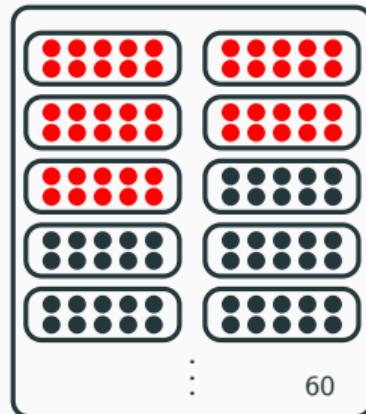
J60



J90

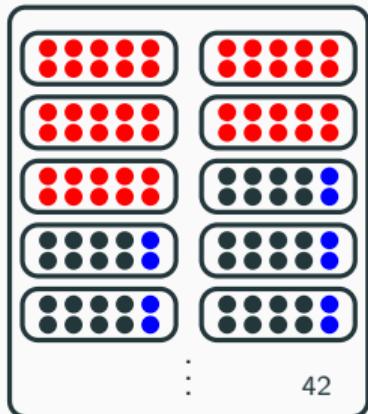


J120

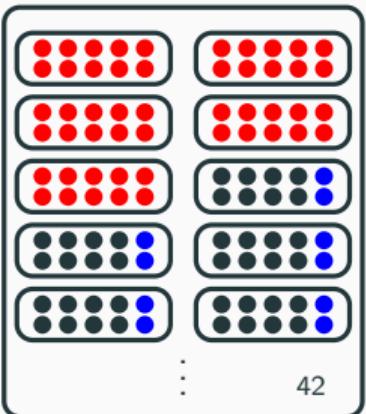


- Unknown

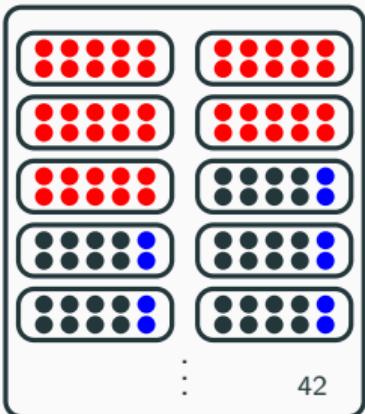
J30



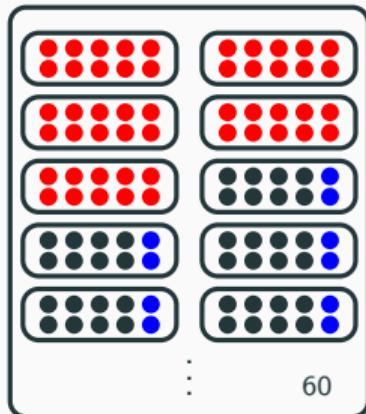
J60



J90



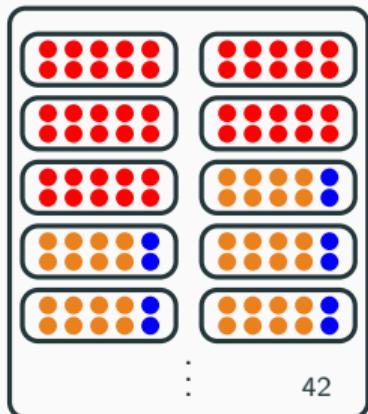
J120



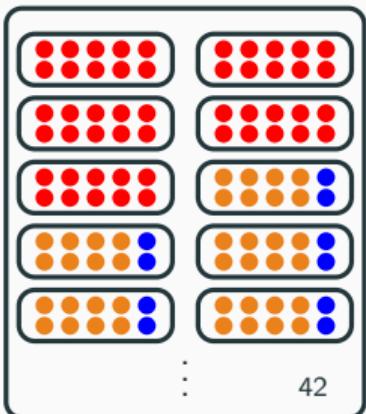
● Unseen

● Unknown

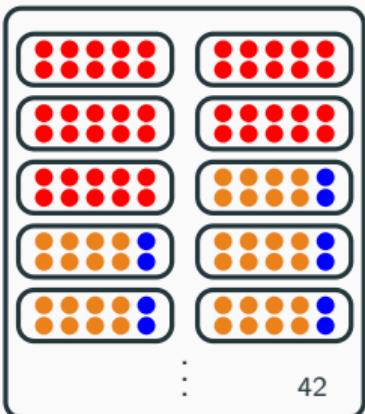
J30



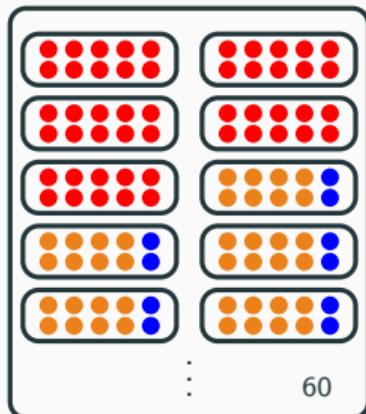
J60



J90



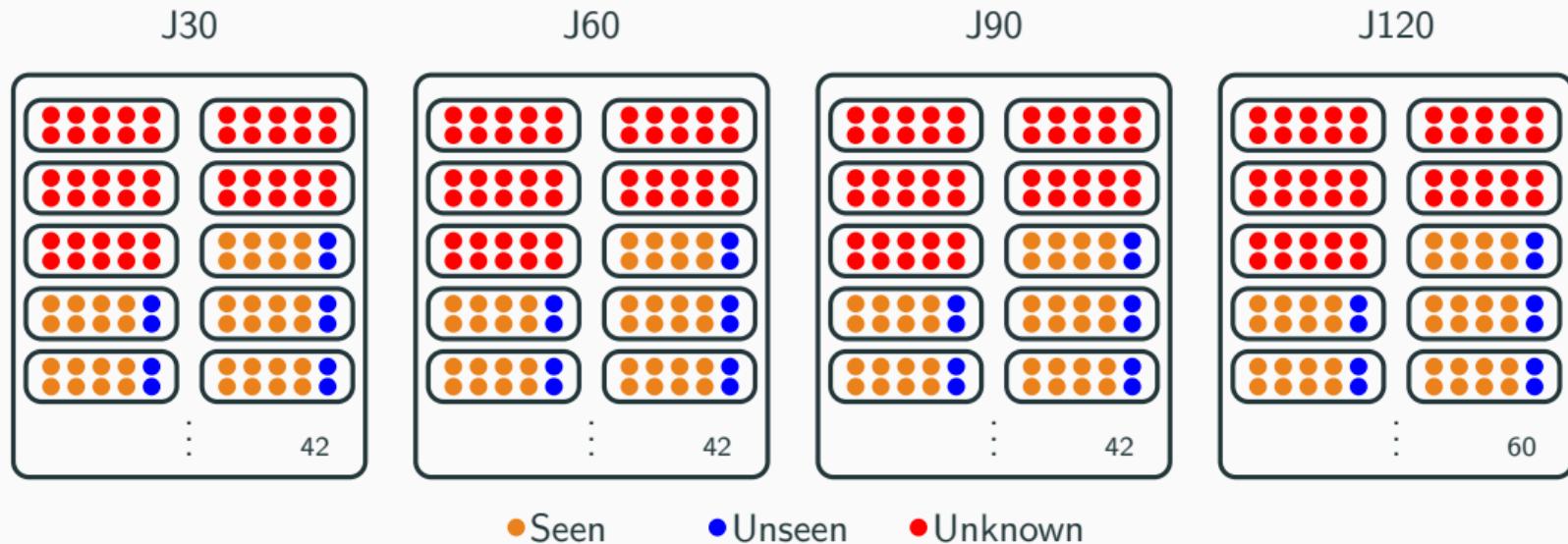
J120



● Seen

● Unseen

● Unknown



- solutions at 1h time out
 - 10-fold cross validation
 - chuffed solver
- two CP models:
 - one with early task first heuristic
 - one with sbps/vsids search heuristic

Quality of the training set

	Model A ("without")				Model B ("with")			
	f1	prec	rec	tn	f1	prec	rec	tn
SEEN _{J120}	0.79	0.89	0.71	0.91	0.71	0.82	0.62	0.87
UNSEEN _{J120}	0.78	0.89	0.70	0.92	0.71	0.83	0.62	0.87
UNKNOWN _{J120}	0.80	0.90	0.72	0.92	0.72	0.84	0.64	0.87
ALL _{J120}	0.79	0.89	0.71	0.91	0.71	0.83	0.62	0.87

	Predictions used as constraints				Predictions used for ordering			
	to=1s	to=1m	to=10m	to=1h	to=1s	to=1m	to=10m	to=1h
Model A	411/163	108/454	24/533	28/526	413/45	172/39	6/25	1/13
Model B	419/152	125/386	26/469	34/459	433/26	179/25	8/17	2/8

Setting: Training on $\leq J120$ instances generated with or without vsids/sbps; evaluation on $J120$ instances, with vsids/sbps

	Model A ("without")				Model B ("with")			
	f1	prec	rec	tn	f1	prec	rec	tn
SEEN _{J120}					62	0.87		
UNSEEN _{J120}					62	0.87		
UNKNOWN _{J120}					64	0.87		
ALL _{J120}					62	0.87		
	t							
Model A	41							
Model B	41							

Takeaway: Use best training set

Worse training metrics

Better use metrics

Setting: Training on $\leq J120$ instances generated with or without vsids/sbps; evaluation on $J120$ instances, with vsids/sbps

Generalizing - models trained with smaller instances

	<i>f1</i>	<i>prec</i>	<i>rec</i>	<i>tn</i>
SEEN _{J120}	0.72	0.82	0.64	0.86
UNSEEN _{J120}	0.72	0.83	0.64	0.87
UNKNOWN _{J120}	0.73	0.83	0.65	0.87
ALL _{J120}	0.72	0.83	0.64	0.87

	Predictions used as constraints				Predictions used for ordering			
	1s	1m	10m	1h	1s	1m	10m	1h
≤J120 train	419/152	125/386	26/469	34/459	433/26	179/25	8/17	2/8
≤J60 train	421/141	119/398	27/484	35/481	430/17	187/18	6/10	1/4

Setting: Training on $\leq J60$ instances; evaluation on $J120$ instances, with vsids/sbps

	$f1$	$prec$	rec	tn
SEEN _{J120}	0.72	0.82	0.64	0.86

Takeaway: very good generalization

Equivalent training metrics

Equivalent use metrics

	1s
$\leq J120$ train	419/1
$\leq J60$ train	421/1

	sed for ordering	
	10m	1h
	8/17	2/8
	6/10	1/4

Setting: Training on $\leq J60$ instances; evaluation on $J120$ instances, with vsids/sbps

Sol 1

Aggregating solutions

Sol 1

Sol 2

Sol 3

Sol 4

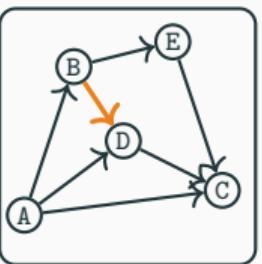
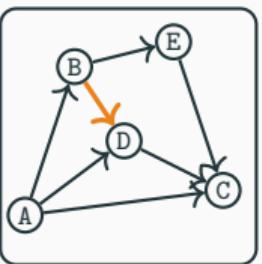
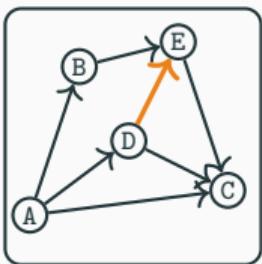
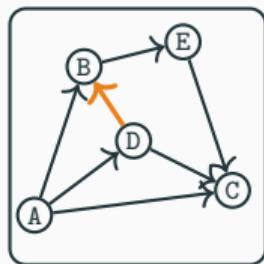
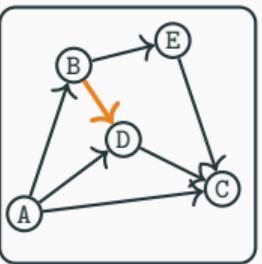
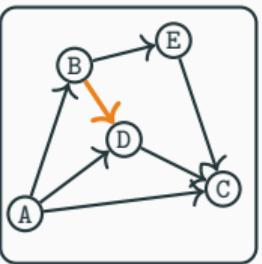
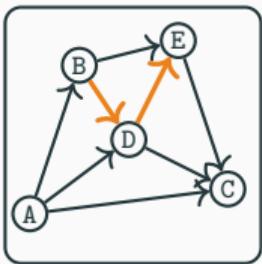
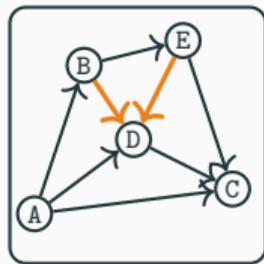
Sol 5

Sol 6

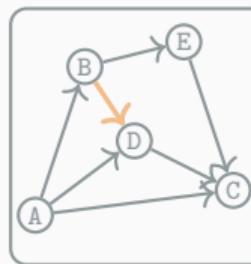
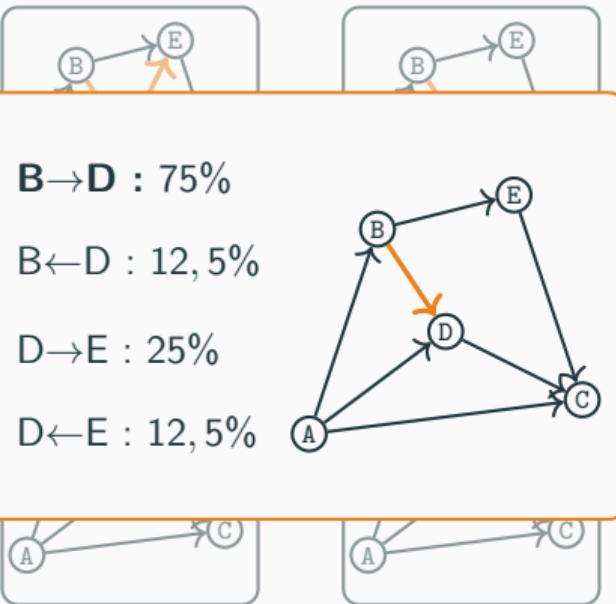
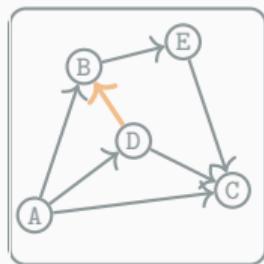
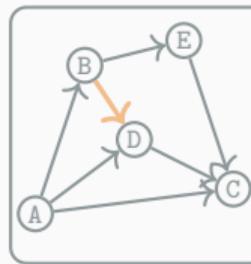
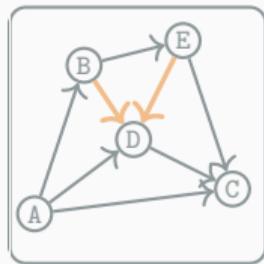
Sol 7

Sol 8

Aggregating solutions



Aggregating solutions



	f1	prec	rec	tn
ALL _{J30}	0.67	0.80	0.57	0.86
ALL _{J60}	0.68	0.79	0.59	0.84
ALL _{J90}	0.67	0.78	0.59	0.83
ALL _{J120}	0.72	0.83	0.64	0.87

	Predictions used as constraints				Predictions used for ordering			
	1s	1m	10m	1h	1s	1m	10m	1h
1-sol	421/141	119/398	27/484	35/481	430/17	187/18	6/10	1/4
Aggregate	436/108	154/332	46/427	48/424	451/0	193/1	7/2	0/2

Setting: Training on $\leq J60$ instances, with aggregate of up to 100 solutions (70% threshold); evaluation on J120 instances, with vsids/sbps

	f1	prec	rec	tn
ALL _{J30}	0.67	0.80	0.57	0.86
ALL _{J60}	0.68	0.79	0.59	0.84

Takeaway: More useful precedences

	1s
1-sol	421/14
Aggregate	436/10

Equivalent training metrics

Improved use metrics

ed for ordering	10m	1h
6/10	1/4	
7/2	0/2	

Setting: Training on $\leq J60$ instances, with aggregate of up to 100 solutions (70% threshold); evaluation on J120 instances, with vsids/sbps

Conclusion



- Solver independent solution
- Good learning capabilities
- Very good generalization, allowing easier dataset generation
- Noise reduction when training on aggregate solutions
- Better earlier solutions



- Other RCPSPs benchmarks
- Other generalization aspects (# resources,...)
- Updating prediction during the search
- Adapt on other problems with underlying graphs

Thank you for listening!

Any questions?

<https://hverhaeghe.bitbucket.io/>