Learning Effect and Compound Activities in High Multiplicity RCPSP : Application to Satellite Production

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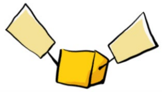
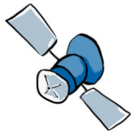
Satellite Assembly Line



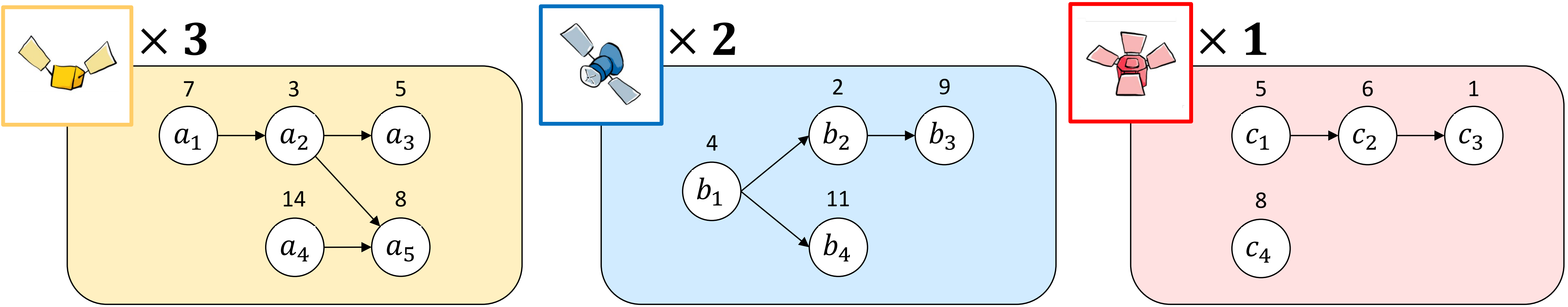
$\times$ 3



$\times$ 2

$\times$ 1

Satellite Assembly Line



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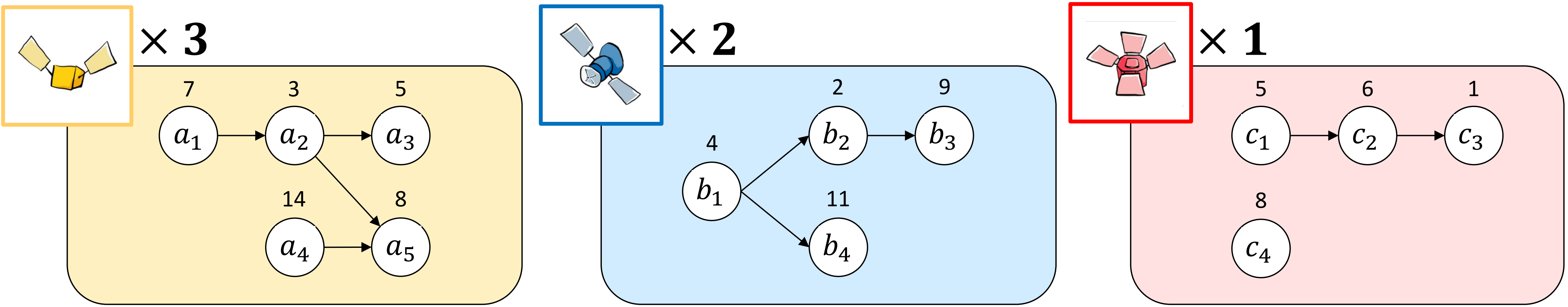

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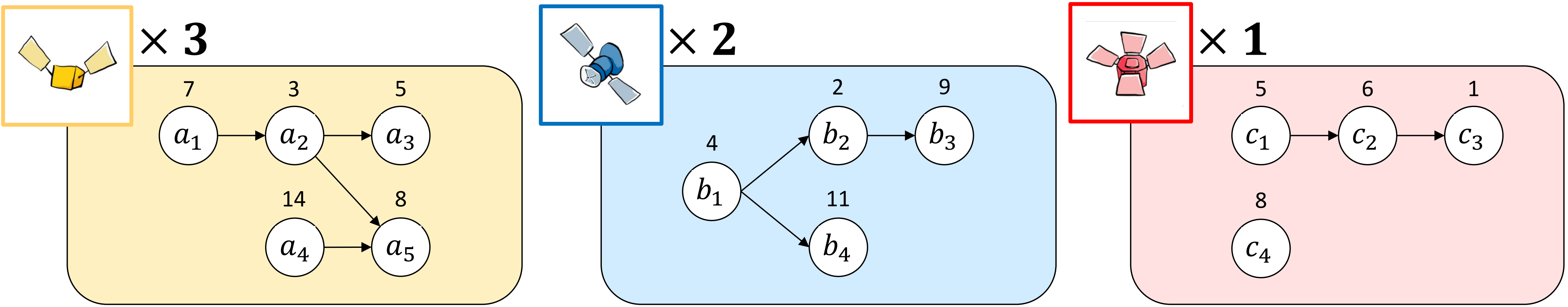

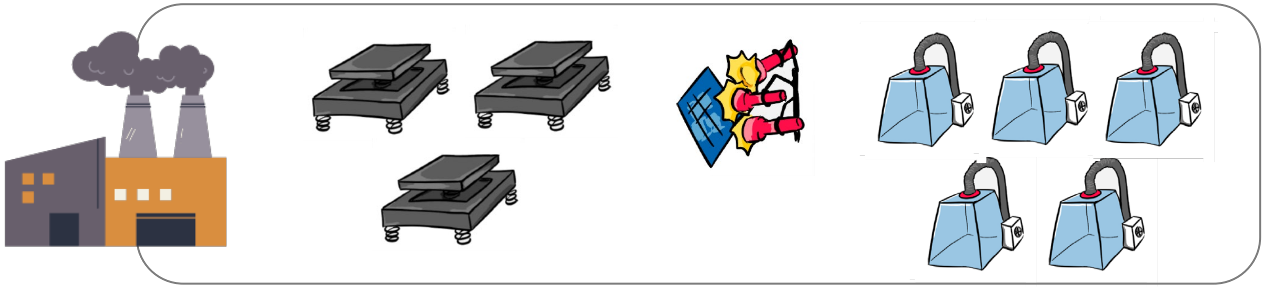

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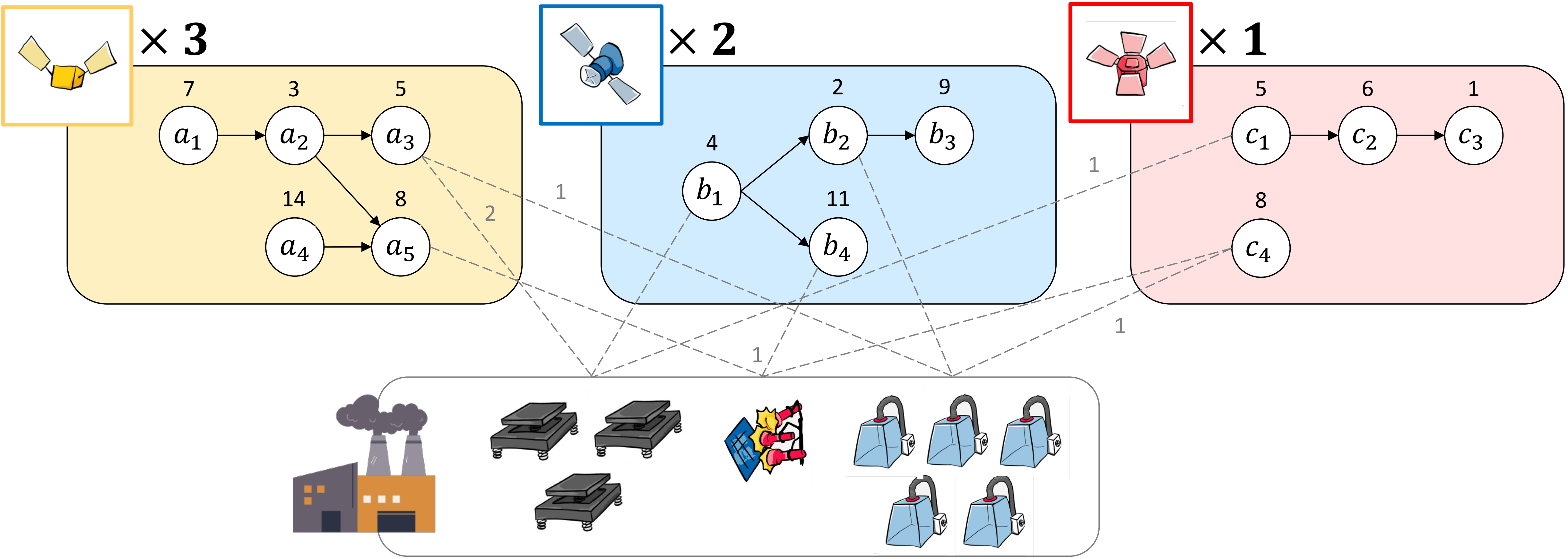

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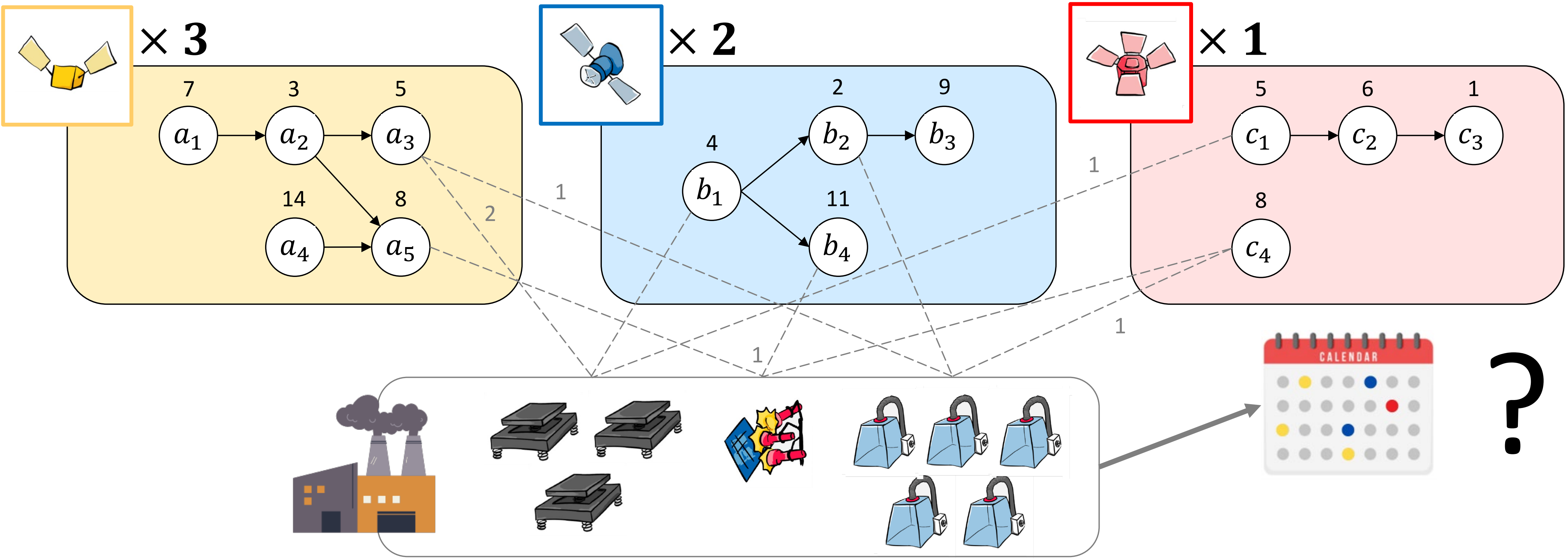

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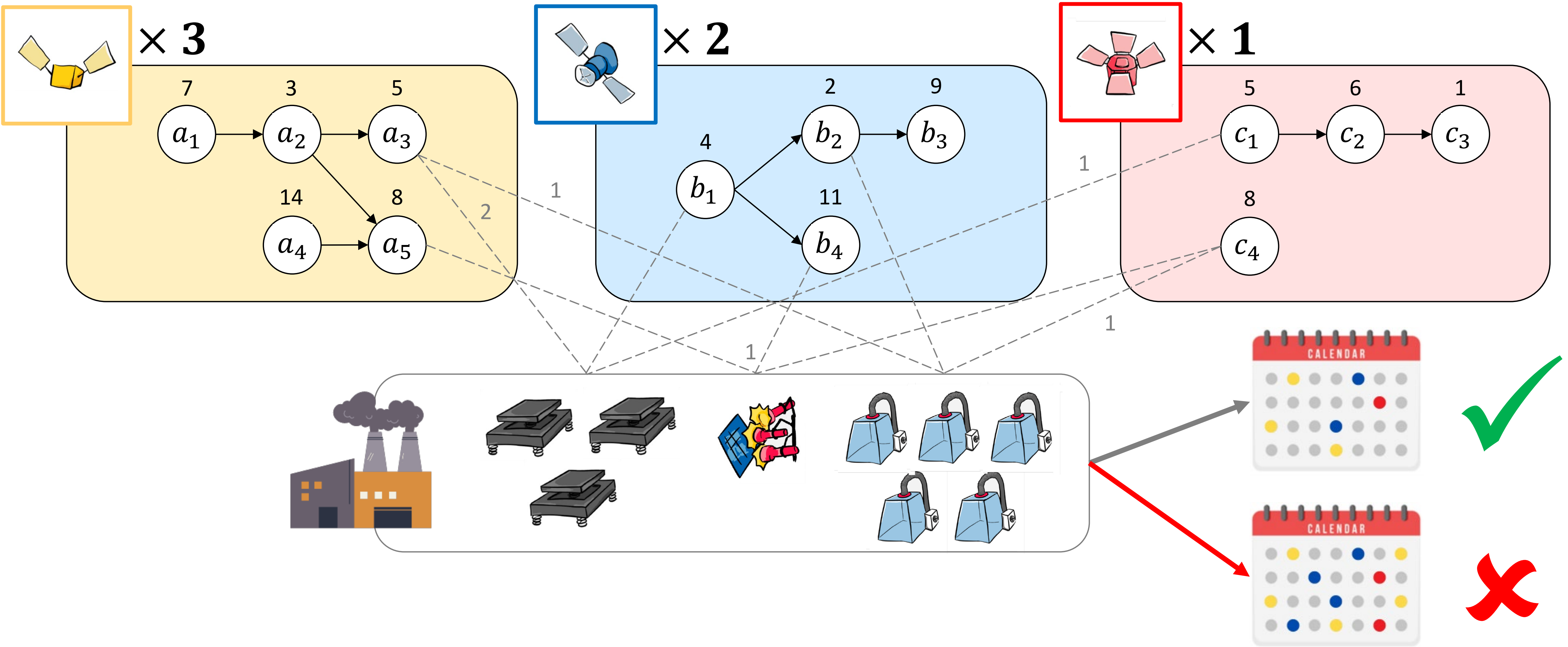

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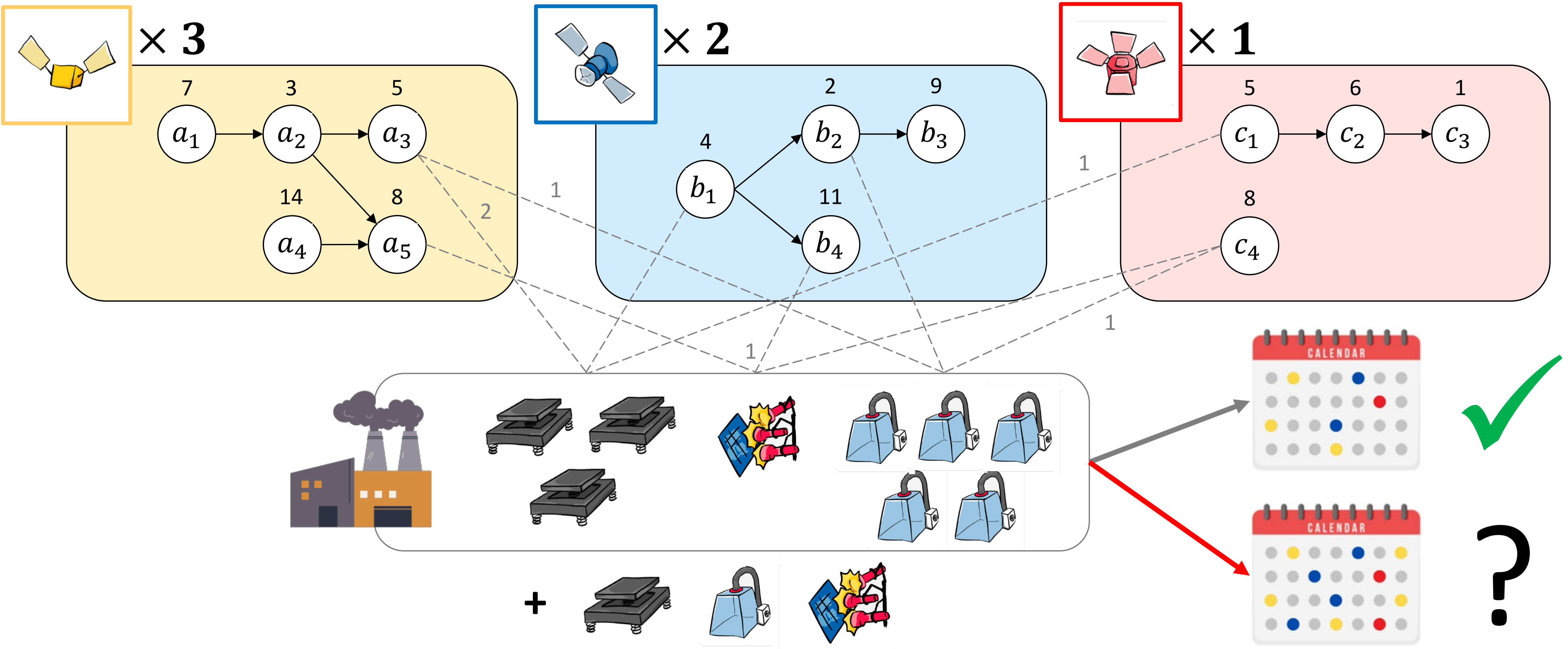
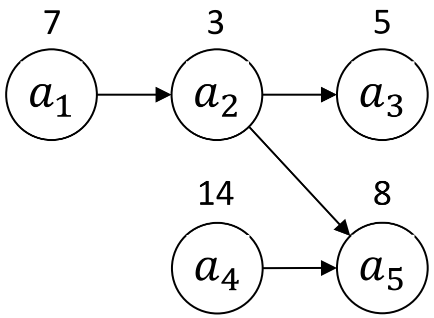
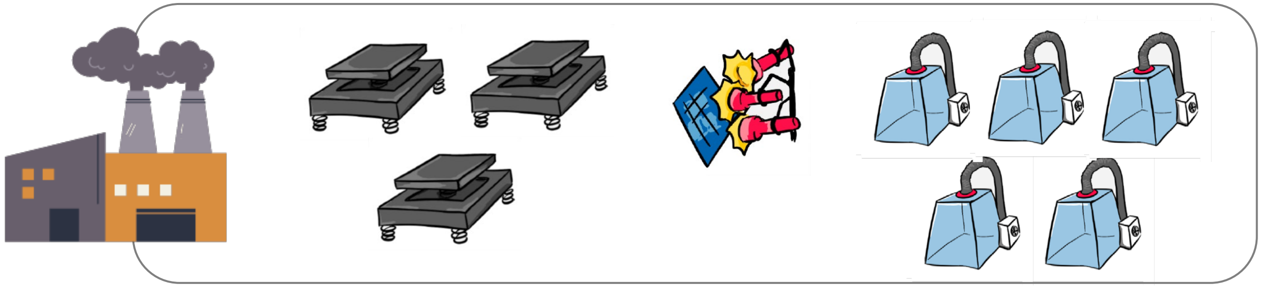


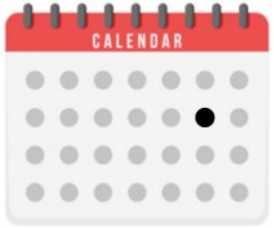
High Multiplicity RCPSP



Activities



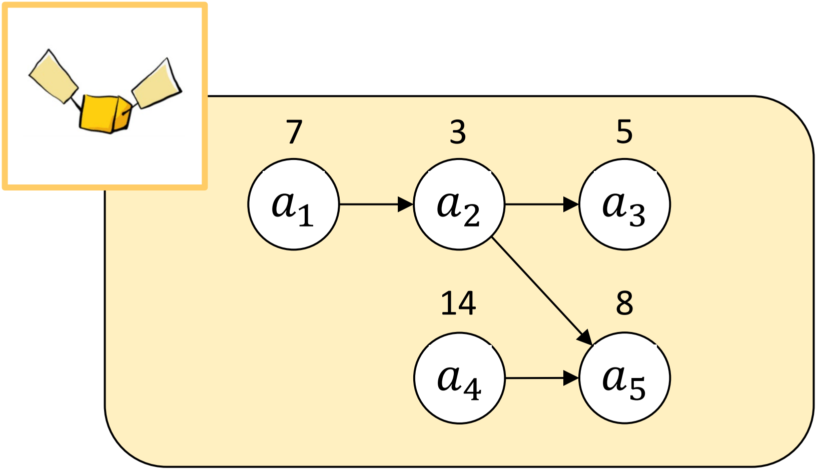
Resources



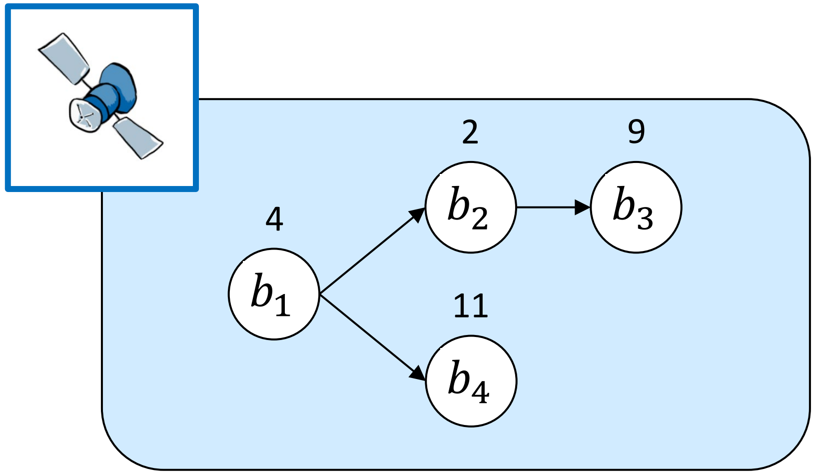
Due date

RCPSP

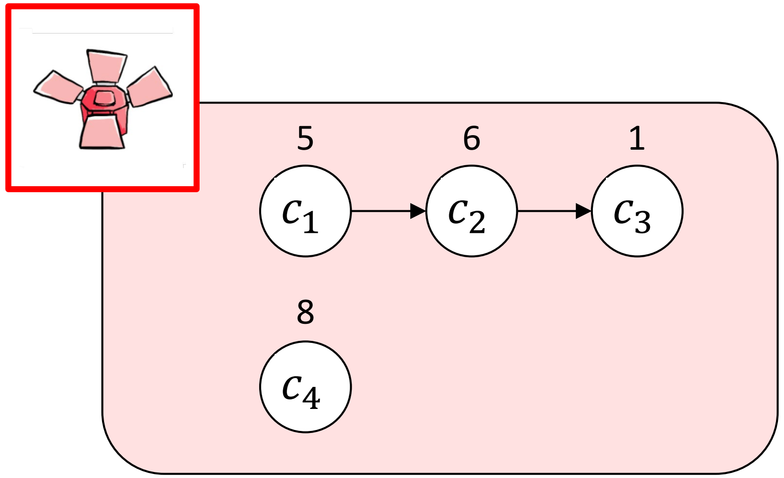
High Multiplicity RCPSP



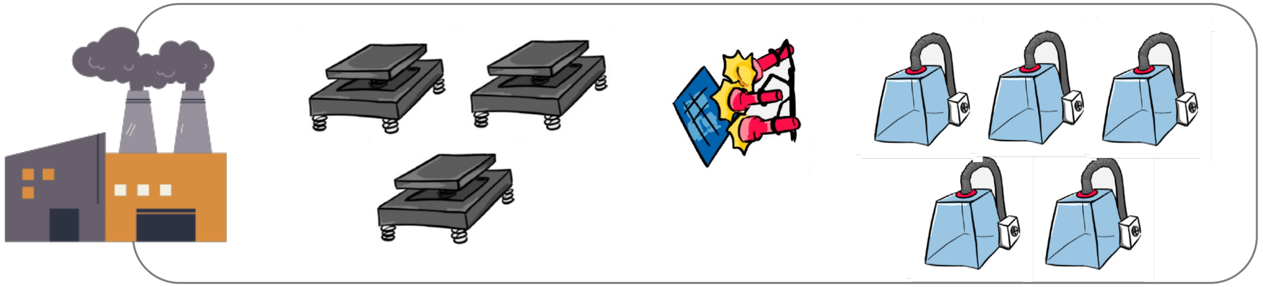
Project 1



Project 2



Project 3

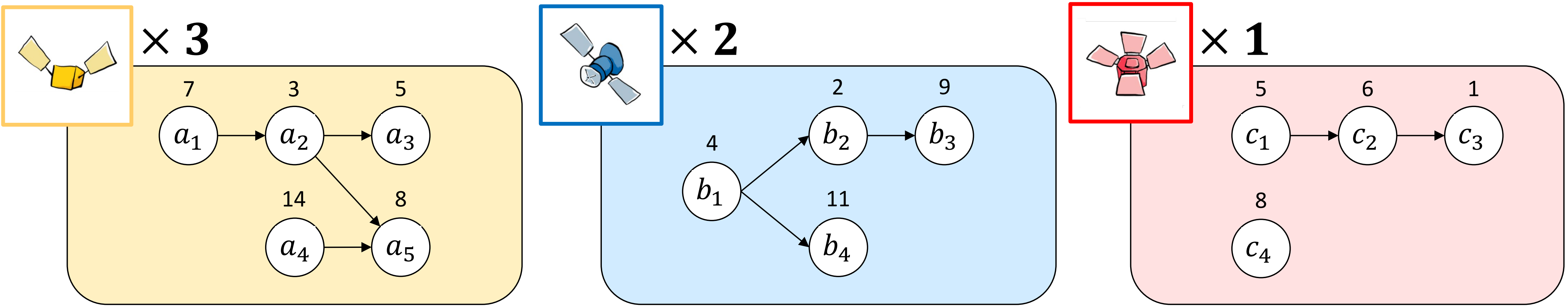


Resources

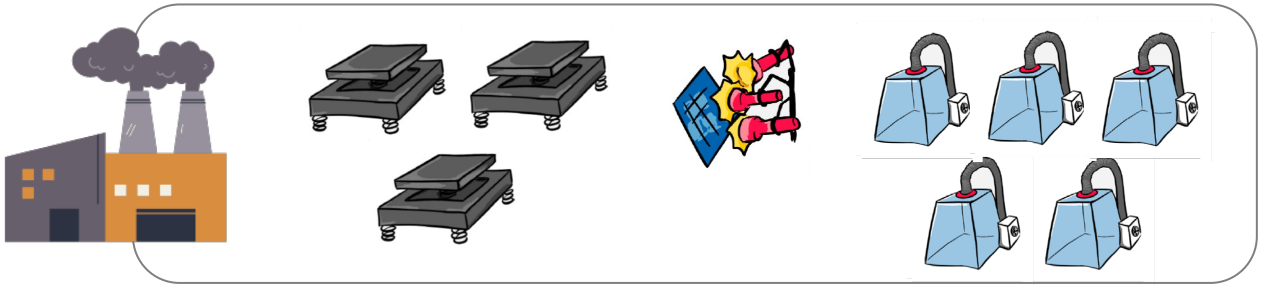
Due dates

MP-RCPSP

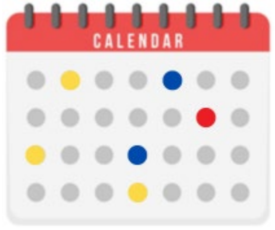
High Multiplicity RCPSP



Class 1 **Class 2** **Class 3**



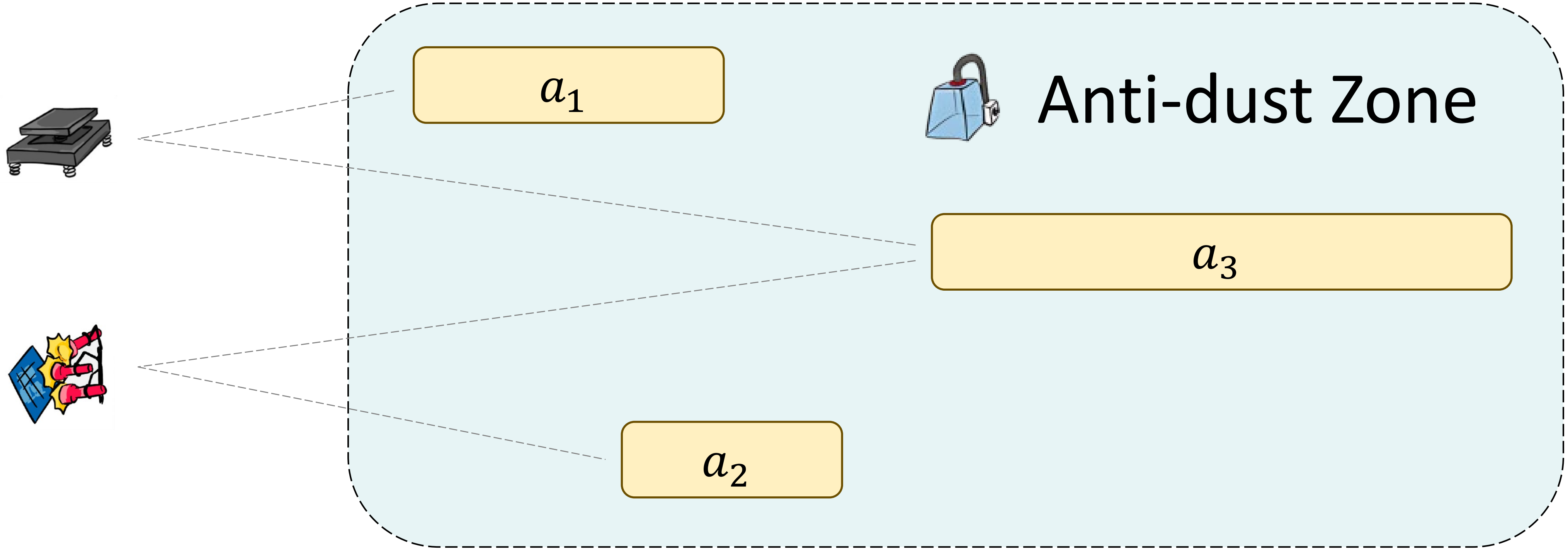
Resources



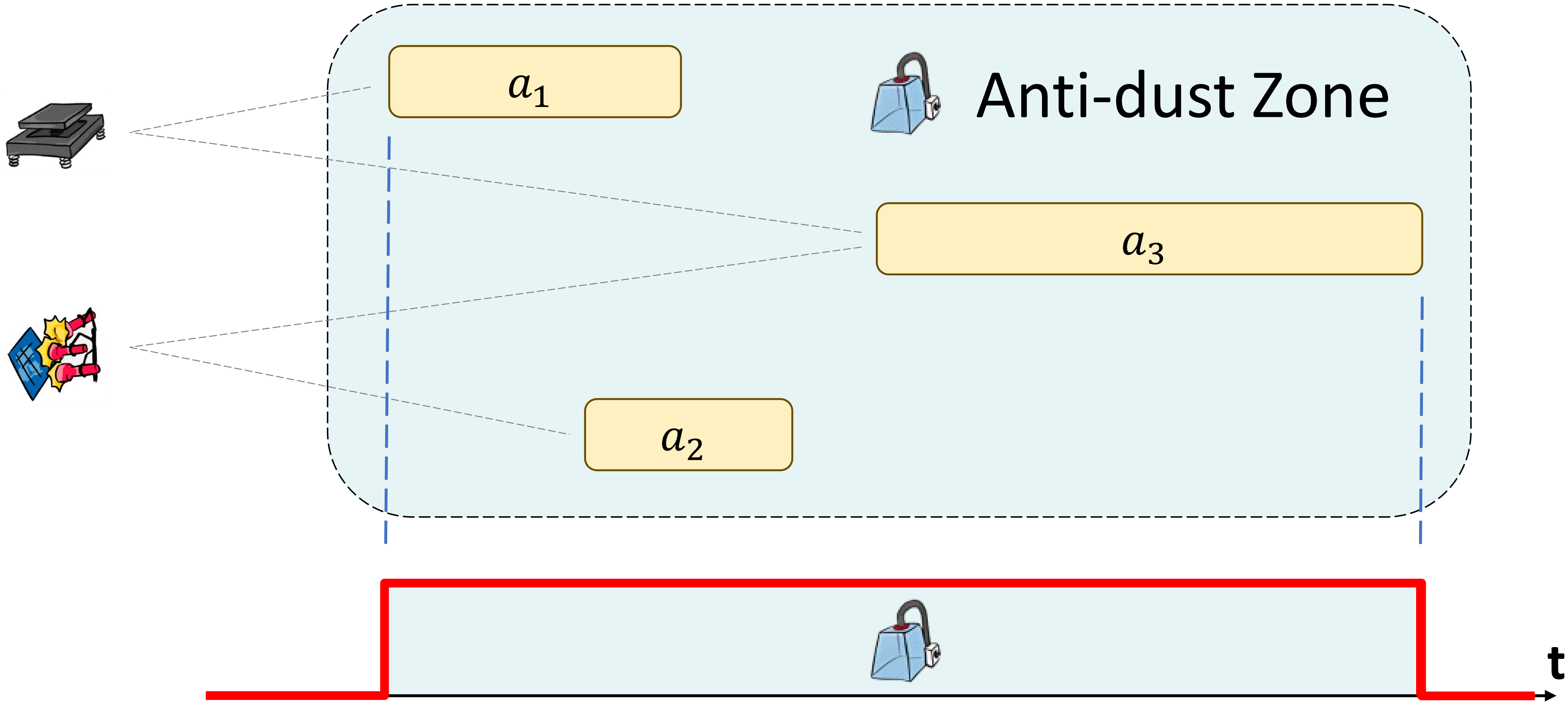
Due dates

HM-RCPSP

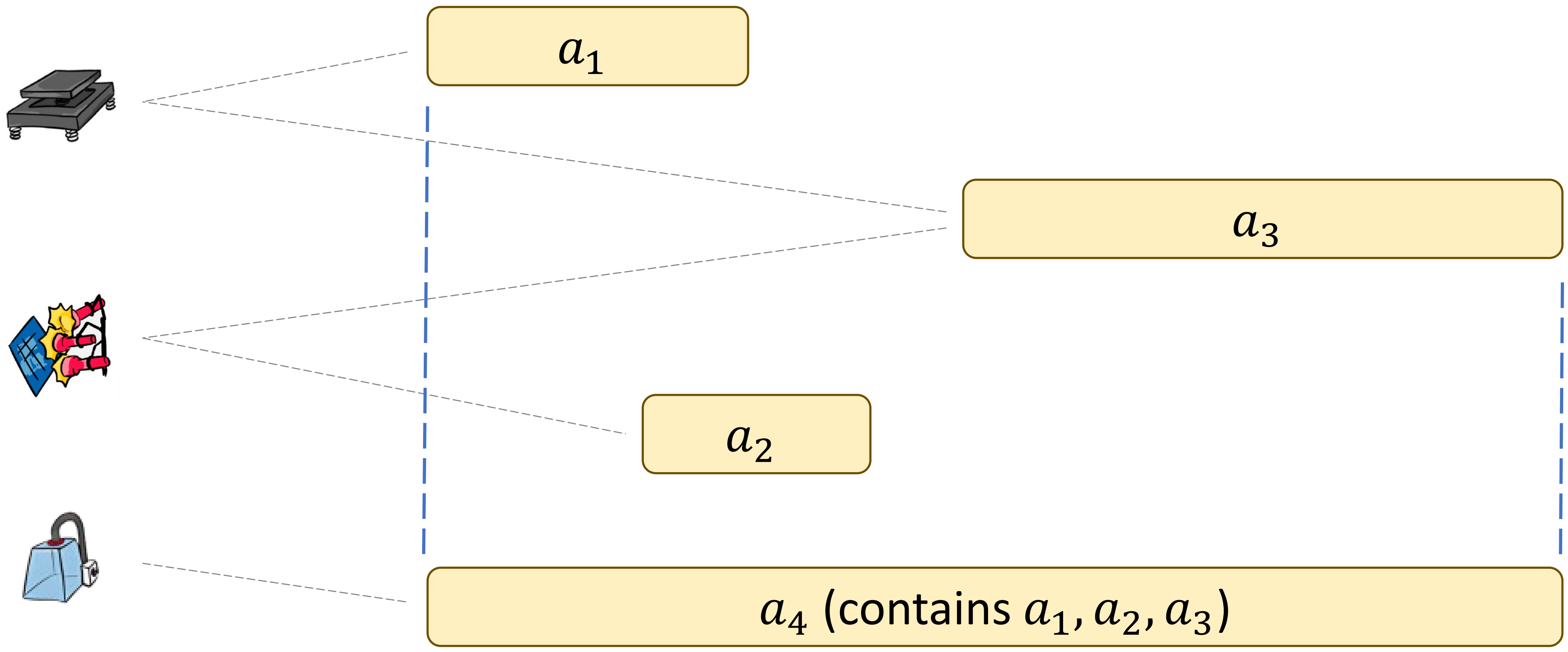
Compound Activity



Compound Activity

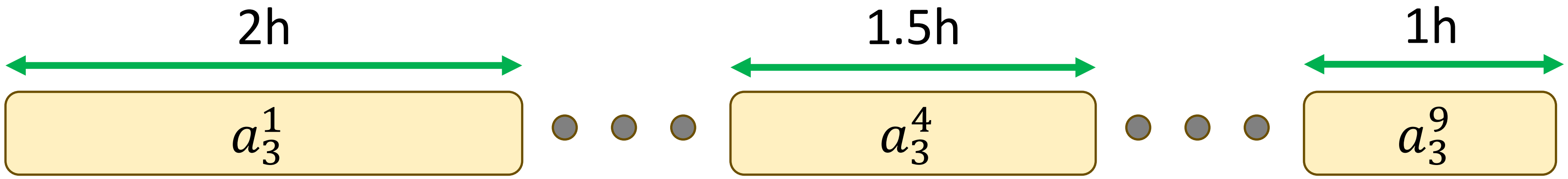


Compound Activity



Learning Effect

- Acquiring experience ⇒ increase in efficiency



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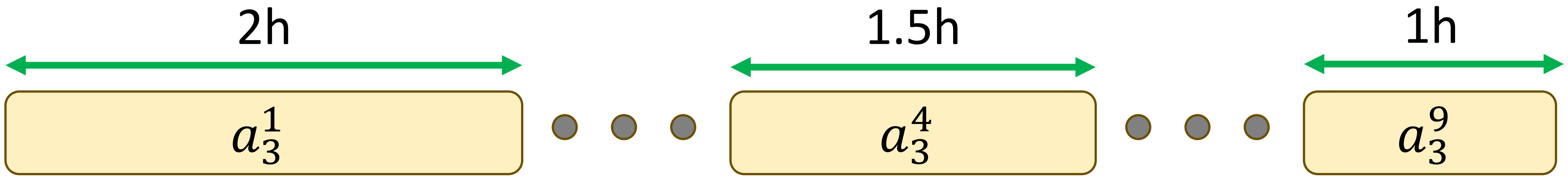

- The execution of activities has an impact on the duration of others

Learning Effect

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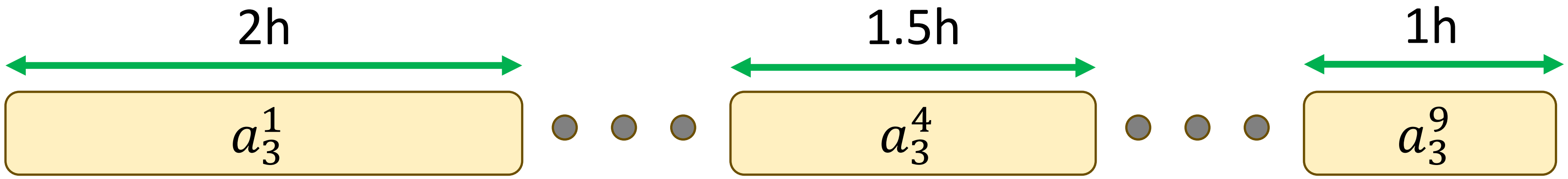

- The execution of activities has an impact on the duration of others

⇒ Projects within class are interdependent

State of the Art

- RCPSP
- MP-RCPSP
- HM-RCPSP

State of the Art

- RCPSP
- MP-RCPSP
- HM-RCPSP

Learning effect

State of the Art

- RCPSP
- MP-RCPSP
- HM-RCPSP

Learning effect

- [Amor 2002]
- [Van Peteghem & Vanhoucke 2015]
- [Qin et al. 2016]
- [Hill et al. 2021]

Objectives

- Bi-objective lexicographic scheduling problem:
  - 1st objective: minimize the sum of projects tardiness
  - 2nd objective: minimize the makespan of the entire schedule

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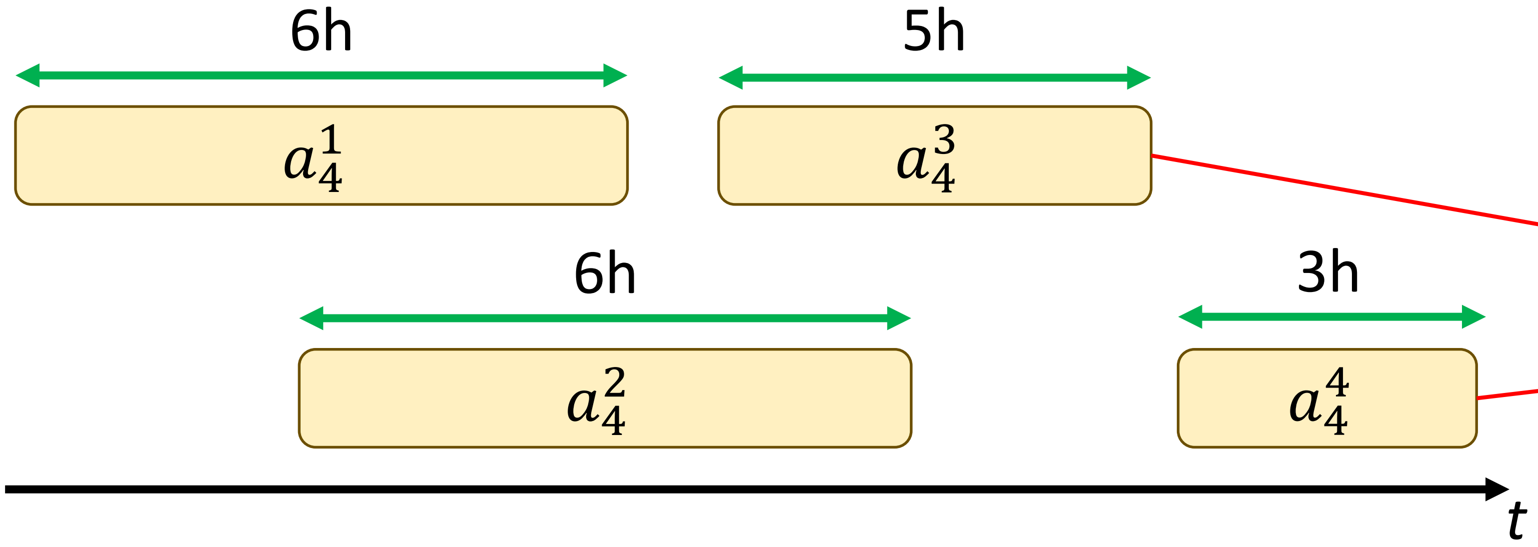
Learning Effect Modeling

- Monotonically decreasing function $dur : \mathbb{N} \rightarrow \mathbb{N}$



Completed executions	Duration (h)
0	6
1	5
2	4
3	3
4	3

HM-RCPSP/L-C

- Problem input:
  - Classes, projects and activities
  - Due dates
  - Learning effect
  - Resources

HM-RCPSP/L-C

- Problem input:
  - Classes, projects and activities
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- Solution: a schedule / the start time of each instance of each activity, which satisfies
  - Precedence relation
  - Composition relation
  - Resource capacities
  - Duration function

HM-RCPSP/L-C

- Problem input:
  - Classes, projects and activities
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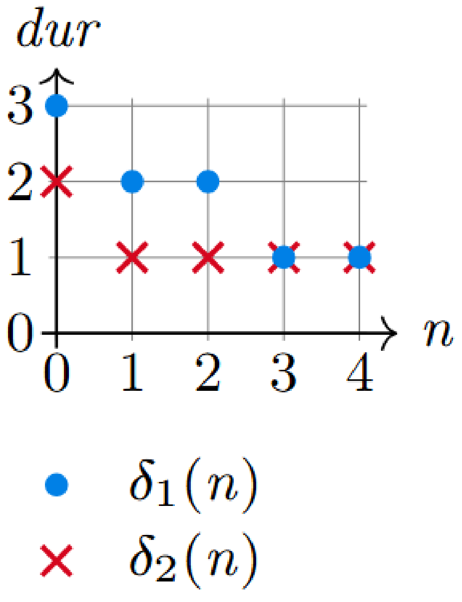
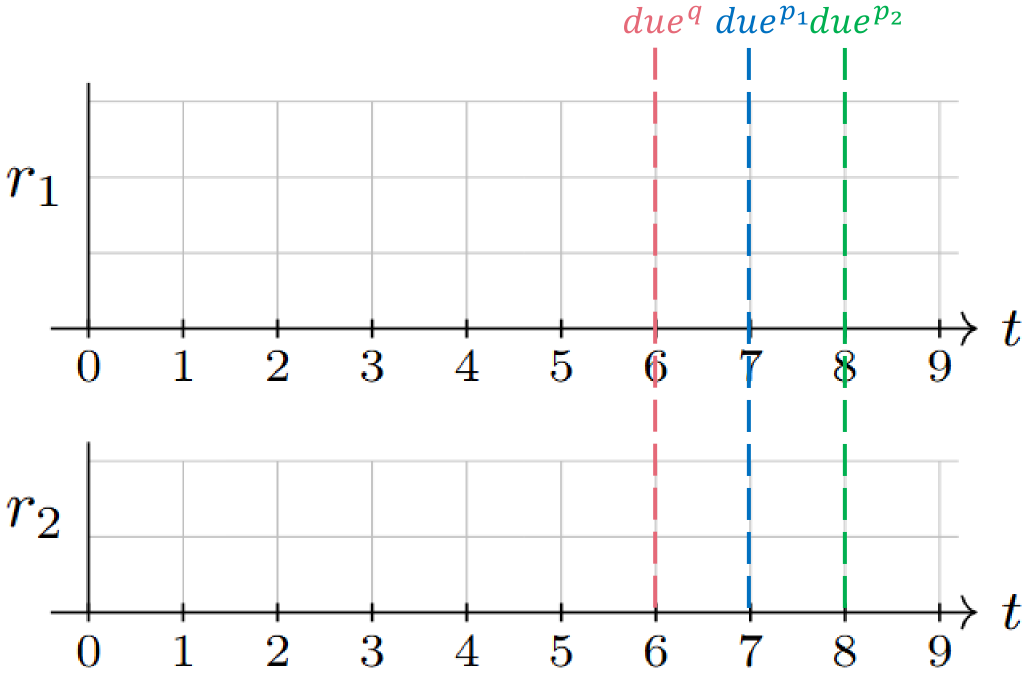
- Solution: a schedule / the start time of each instance of each activity, which satisfies
  - Precedence relation
  - Composition relation
  - Resource capacities
  - Duration function
- Optimization criteria: sum of tardiness & makespan

Example

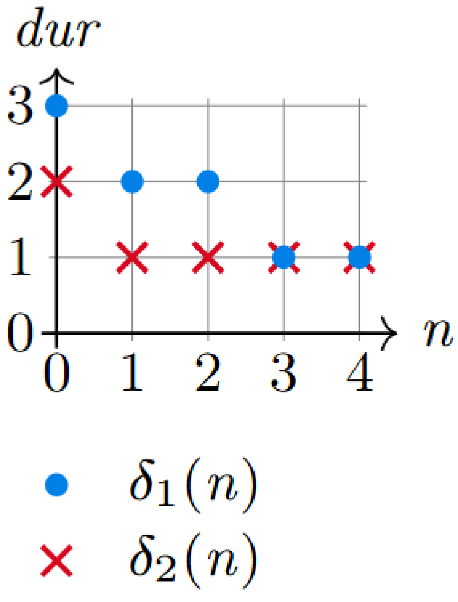
$\mathcal{C}$	$\mathcal{A}_c$	dur_a	r_1	r_2
c_1 p_1 p_2	a	δ_1	1	0
	b	δ_2	0	1
	c	δ_1	0	1
	d	-	1	0
c_2 q	e	δ_2	0	1
	f	δ_1	1	0
	g	-	1	0

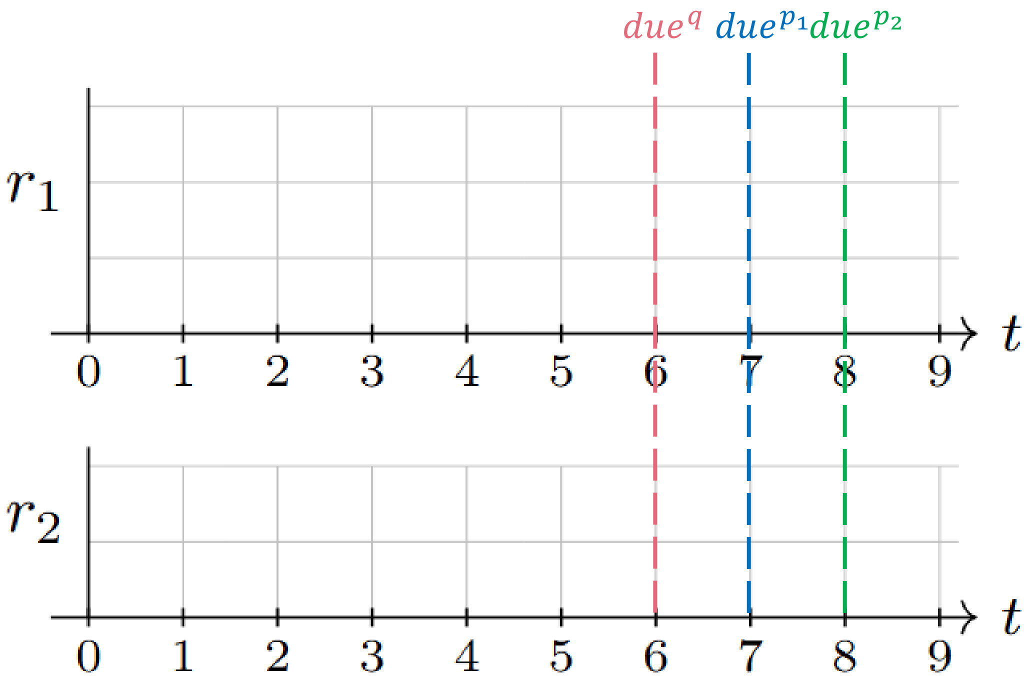




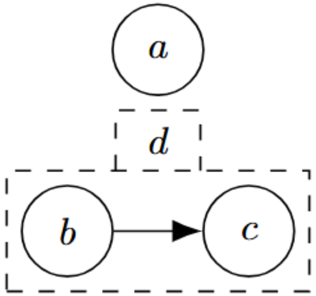
Example

$\mathcal{C}$	$\mathcal{A}_c$	dur_a	r_1	r_2
c_1 p_1 p_2	a	δ_1	1	0
	b	δ_2	0	1
	c	δ_1	0	1
	d	-	1	0
c_2 q	e	δ_2	0	1
	f	δ_1	1	0
	g	-	1	0

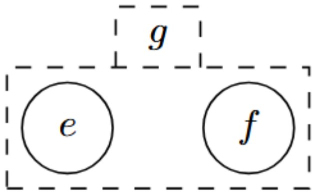




c_1 :

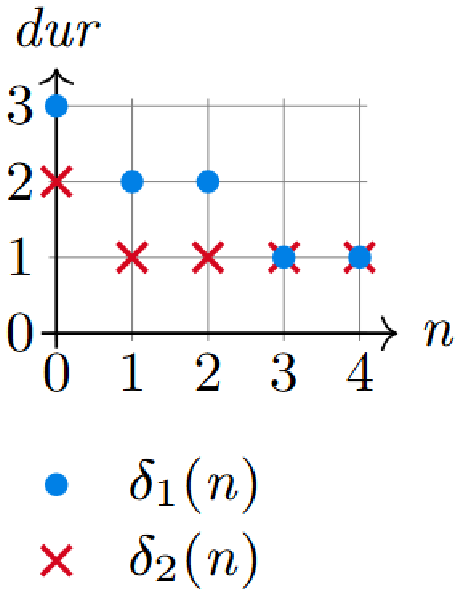


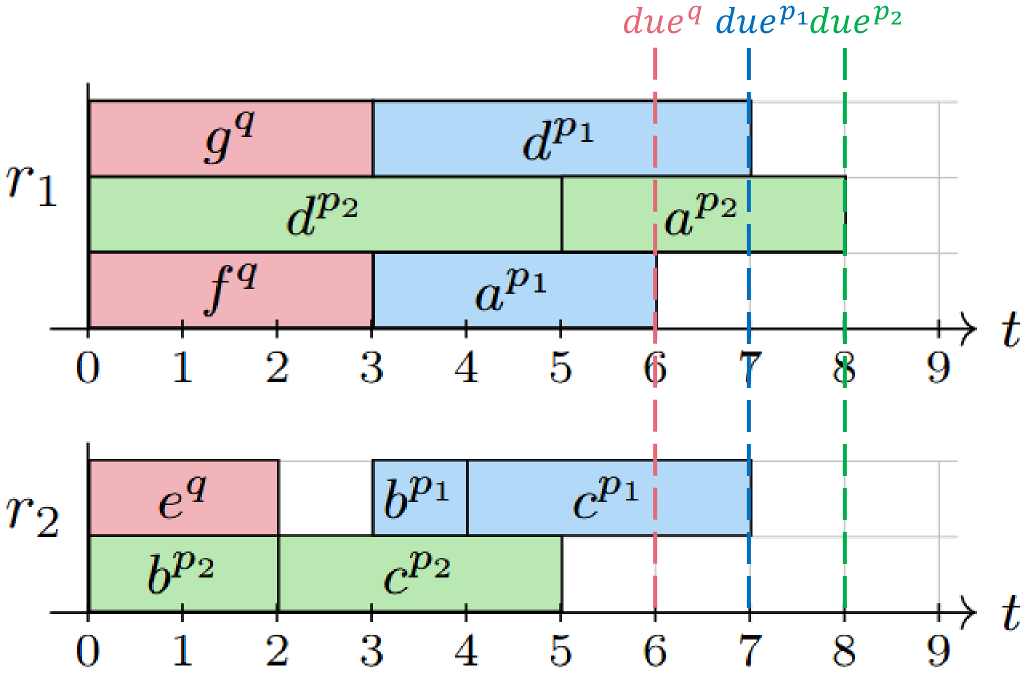
c_2 :



Example

$\mathcal{C}$	$\mathcal{A}_c$	dur_a	r_1	r_2
c_1 (p_1 p_2)	a	δ_1	1	0
	b	δ_2	0	1
	c	δ_1	0	1
	d	-	1	0
c_2 (q)	e	δ_2	0	1
	f	δ_1	1	0
	g	-	1	0





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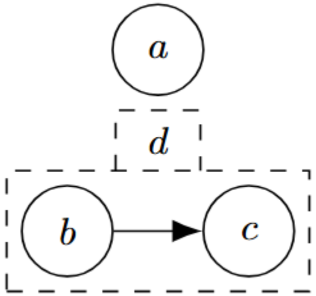
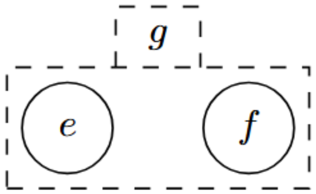
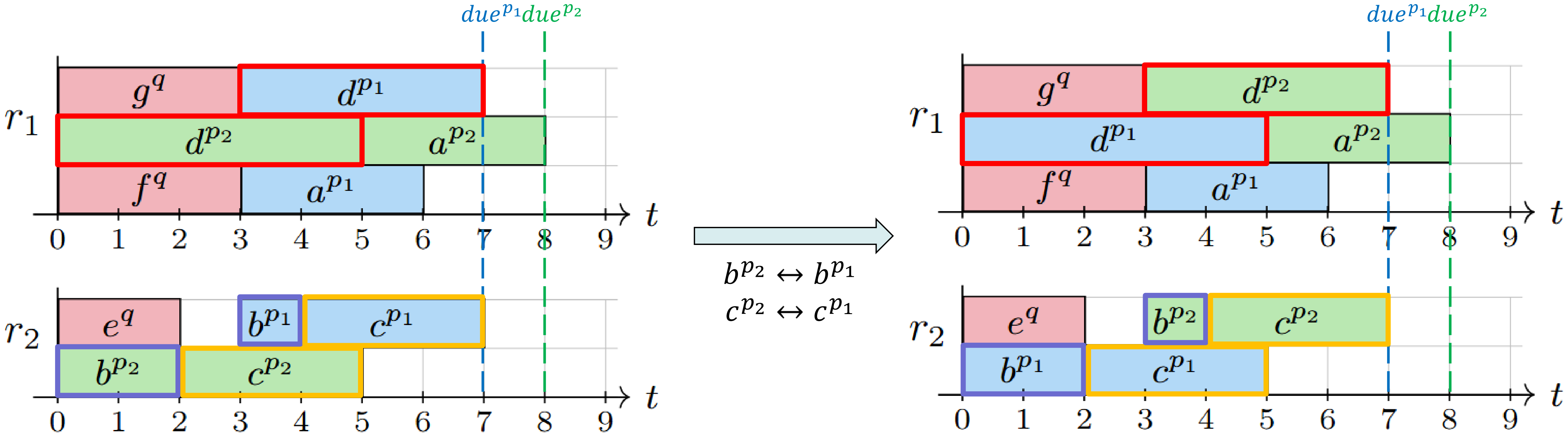


c_2 :



Symmetry Breaking



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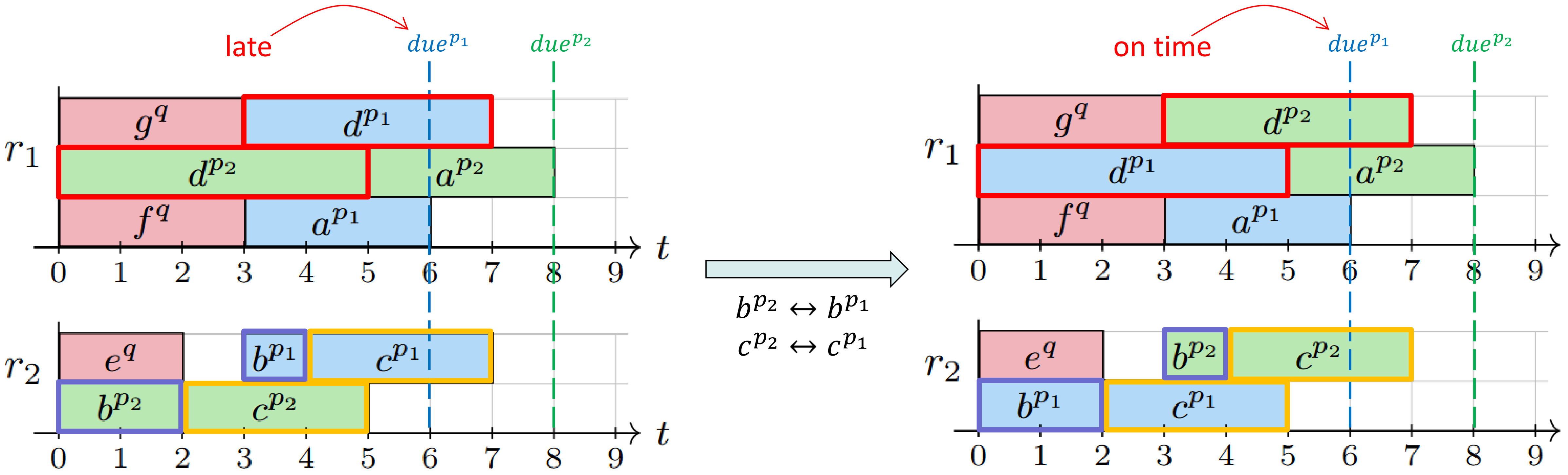

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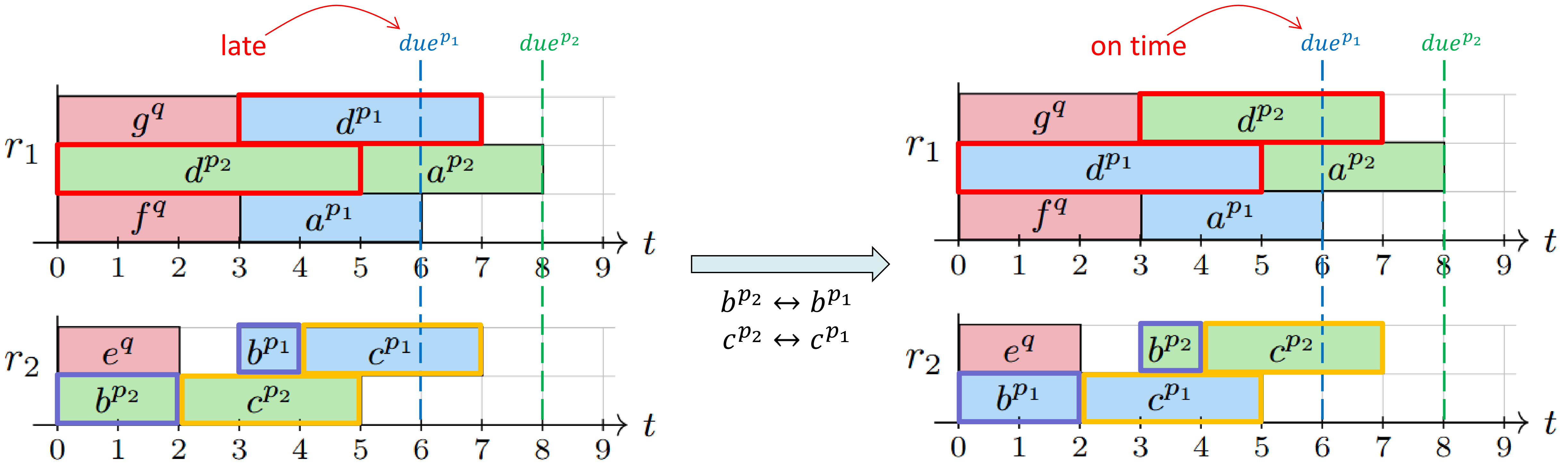
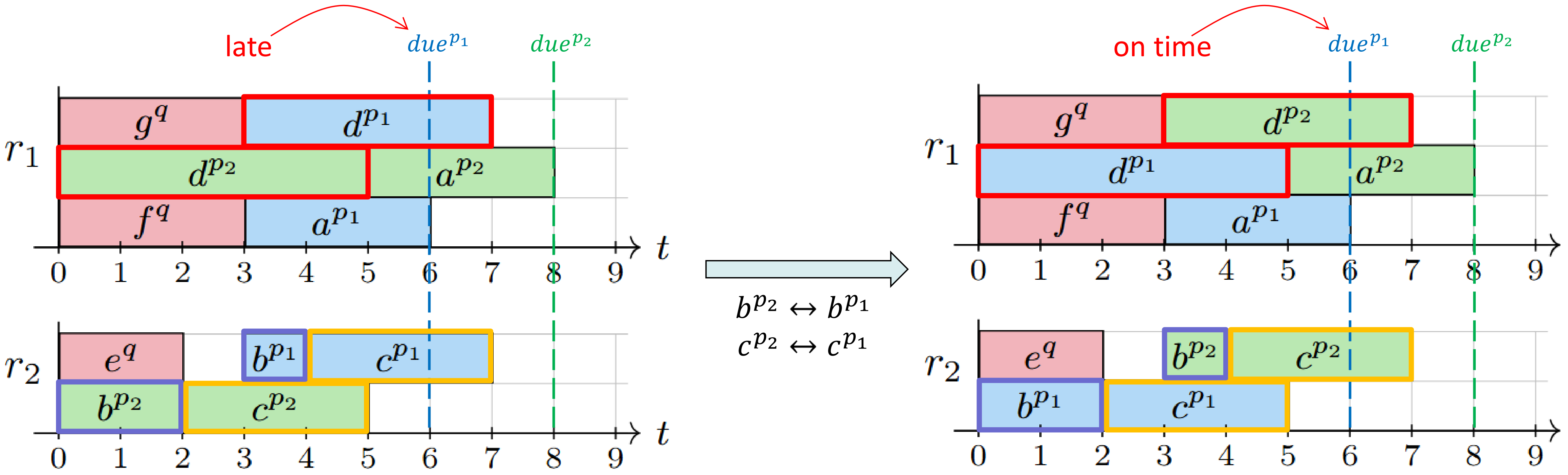


Theorem:

$$\boldsymbol{IF}\ due^{p_1} \leq due^{p_2}\ \boldsymbol{THEN}\ criteria(b^{p_1}\ before\ b^{p_2}) \leq criteria(b^{p_2}\ before\ b^{p_1})$$

Symmetry Breaking



Theorem:

$$\boldsymbol{IF}\ due^{p_1} \leq due^{p_2}\ \boldsymbol{THEN}\ criteria(b^{p_1}\ before\ b^{p_2}) \leq criteria(b^{p_2}\ before\ b^{p_1})$$

➡ Activities are performed in order of due date for same-class projects

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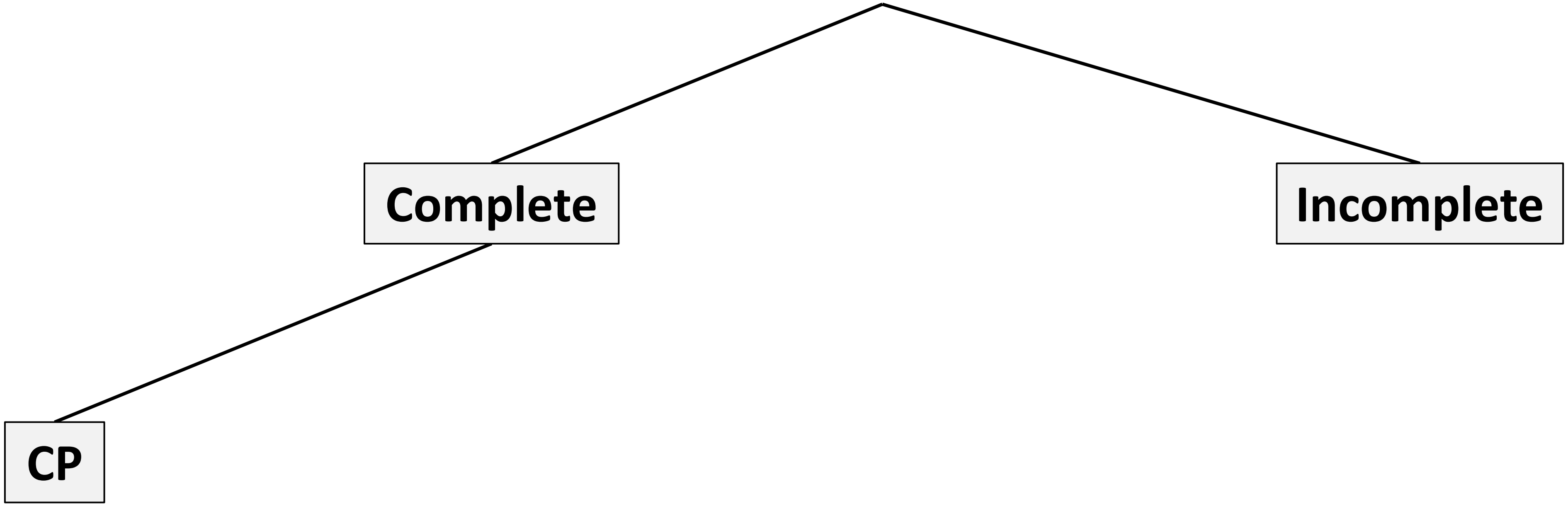
Solving Approaches

Complete

Incomplete

Solving Approaches



Constraint Programming

For each activity a of each project p:

- Interval variable $\mathbf{itv}_{a,p}$ contains properties of this activity instance (starting time, duration)
- Integer variable $\mathbf{n}_{a,p}$ indicates the number of executions that have already been completed of this activity instance

Constraint Programming

$$minimize \left(\underbrace{\sum_{c \in C, p \in I_c, a \in A_c} \max(0, \mathrm{endOf}\left(\mathrm{itv}_{a,p}\right) - due_p)}_{\text{Tardiness}}, \underbrace{\max_{c \in C, p \in I_c, a \in A_c} \mathrm{endOf}\left(\mathrm{itv}_{a,p}\right)}_{\text{Makespan}} \right)$$

Constraint Programming

$$minimize \left(\underbrace{\sum_{c \in C, p \in I_c, a \in A_c} \max\left(0, \mathrm{endOf}\left(\mathrm{itv}_{a,p}\right) - due_p\right),}_{\text{Tardiness}} \underbrace{\max_{c \in C, p \in I_c, a \in A_c} \mathrm{endOf}\left(\mathrm{itv}_{a,p}\right)}_{\text{Makespan}} \right)$$

Classical RCPSP

$$\forall r \in R \qquad \sum_{c \in C, p \in I_c, a \in A_c} \mathrm{pulse}\left(\mathbf{itv}_{a,p}, cons_{r,a}\right) \leq capa_r \qquad (1)$$

$$\forall c \in C, \forall p \in I_c, \forall (a,b) \in Prec_c \qquad \mathrm{endBeforeStart}\left(\mathbf{itv}_{a,p}, \mathbf{itv}_{b,p}\right) \qquad (2)$$

Constraint Programming

$$minimize \left(\underbrace{\sum_{c\in C, p\in I_c, a\in A_c} \max\left(0, \mathrm{endOf}\left(\mathrm{itv}_{a,p}\right) - due_p\right)}_{\text{Tardiness}}, \underbrace{\max_{c\in C, p\in I_c, a\in A_c} \mathrm{endOf}\left(\mathrm{itv}_{a,p}\right)}_{\text{Makespan}} \right)$$

Classical RCPSP

$$\forall r \in R \qquad \textstyle\sum_{c\in C, p\in I_c, a\in A_c} \mathrm{pulse}\left(\mathbf{itv}_{a,p}, cons_{r,a}\right) \le capa_r \qquad (1)$$

$$\forall c \in C, \forall p \in I_c, \forall (a,b) \in Prec_c \qquad \mathrm{endBeforeStart}\left(\mathbf{itv}_{a,p}, \mathbf{itv}_{b,p}\right) \qquad (2)$$

Compound Activities

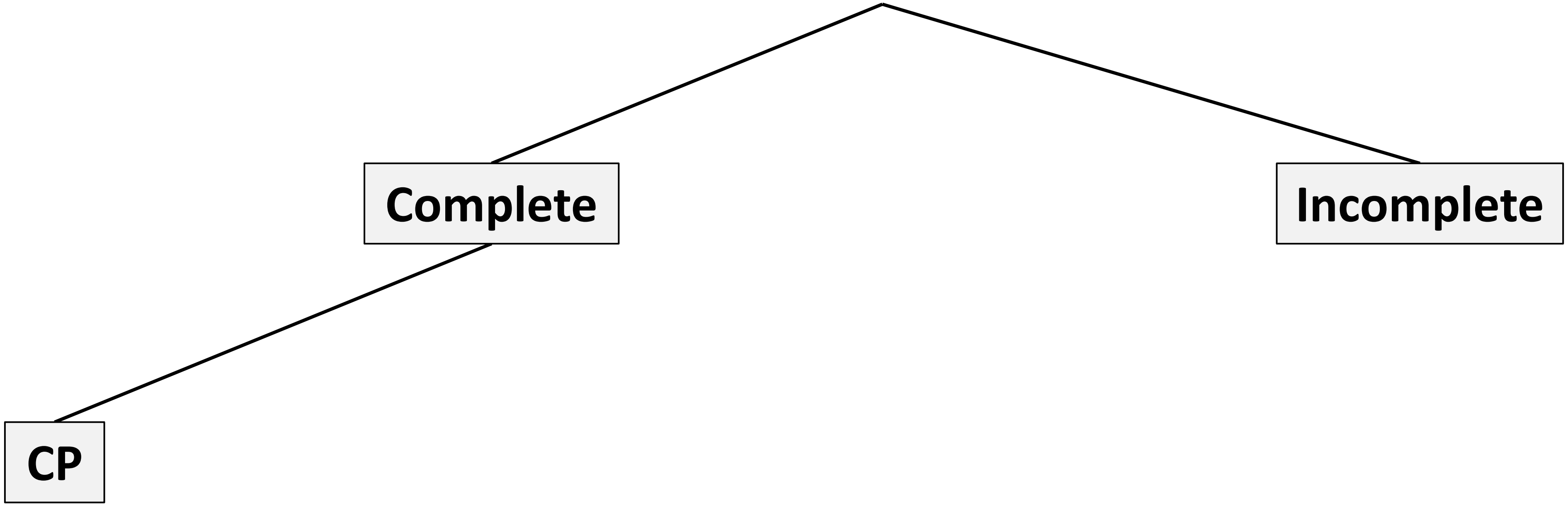
$$\forall c \in C, \forall p \in I_c, \forall a \in A_c^{Comp} \qquad \mathrm{span}\left(\mathbf{itv}_{a,p}, \left\{\mathbf{itv}_{b,p} \middle| (a,b) \in Comp_c\right\}\right) \qquad (3)$$

Constraint Programming

$$minimize \left(\underbrace{\sum_{c \in C, p \in I_c, a \in A_c} \max\left(0, \mathrm{endOf}\left(\mathrm{itv}_{a,p}\right) - due_p\right)}_{\text{Tardiness}}, \underbrace{\max_{c \in C, p \in I_c, a \in A_c} \mathrm{endOf}\left(\mathrm{itv}_{a,p}\right)}_{\text{Makespan}} \right)$$

Classical RCPSP	$\forall r \in R$	$\sum_{c \in C, p \in I_c, a \in A_c} \mathrm{pulse}\left(\mathbf{itv}_{a,p}, cons_{r,a}\right) \leq capa_r$	(1)
	$\forall c \in C, \forall p \in I_c, \forall (a,b) \in Prec_c$	$\mathrm{endBeforeStart}\left(\mathbf{itv}_{a,p}, \mathbf{itv}_{b,p}\right)$	(2)
Compound Activities	$\forall c \in C, \forall p \in I_c, \forall a \in A_c^{Comp}$	$\mathrm{span}\left(\mathbf{itv}_{a,p}, \left\{\mathbf{itv}_{b,p} \middle\| (a,b) \in Comp_c\right\}\right)$	(3)
Learning Effect	$\forall c \in C, \forall p \in I_c, \forall a \in A_c^{Atom}$	$\mathbf{n}_{a,p} = \sum_{q \in I_c} \left(\mathrm{endOf}\left(\mathbf{itv}_{a,q}\right) \leq \mathrm{startOf}\left(\mathbf{itv}_{a,p}\right)\right)$	(4)
	$\forall c \in C, \forall p \in I_c, \forall a \in A_c^{Atom}$	$\mathrm{lengthOf}\left(\mathbf{itv}_{a,p}\right) = dur_a\left(\mathbf{n}_{a,p}\right)$	(5)

Solving Approaches



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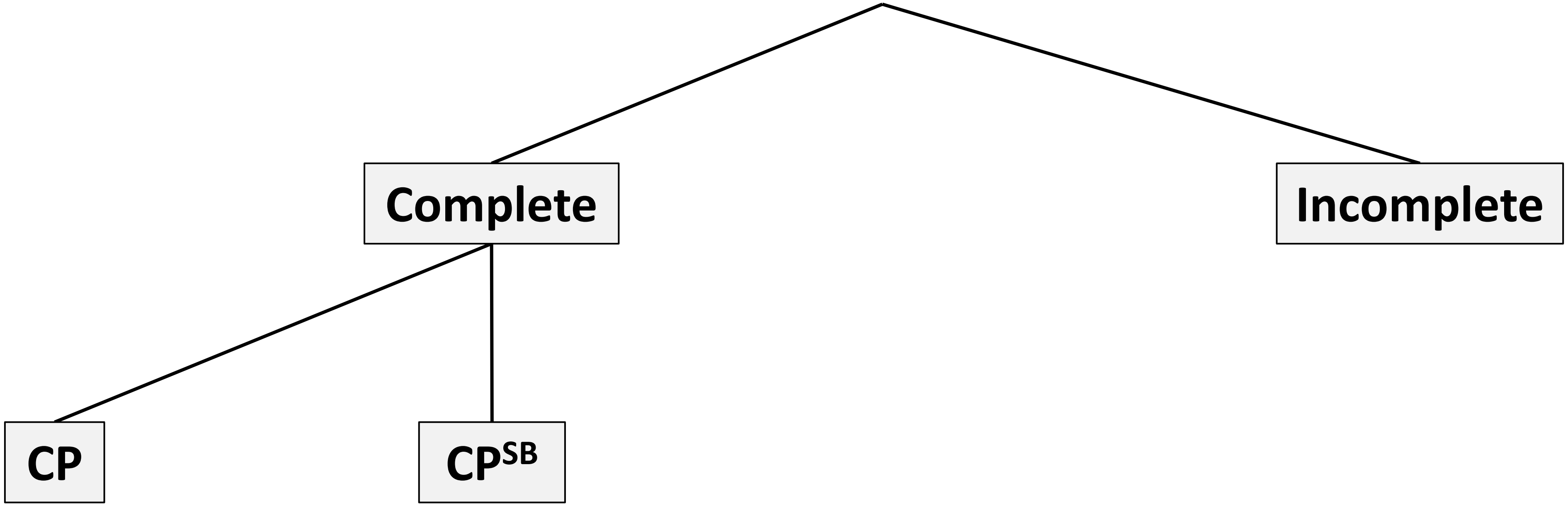

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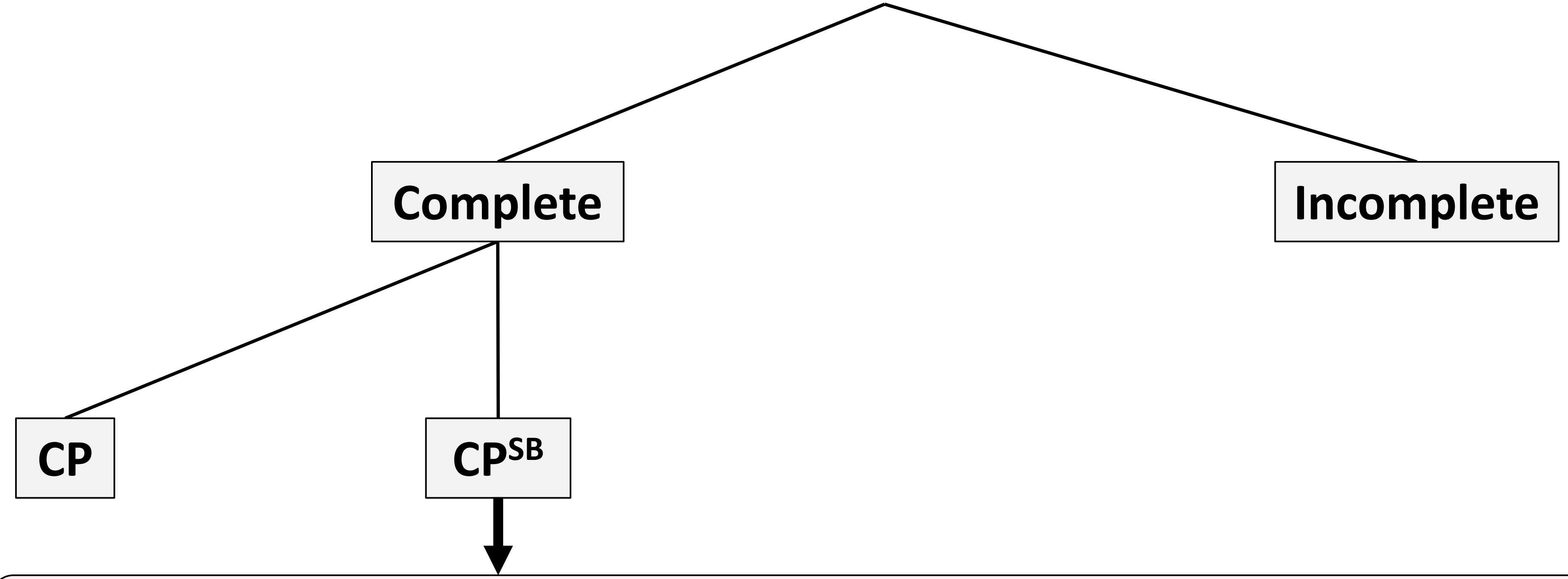
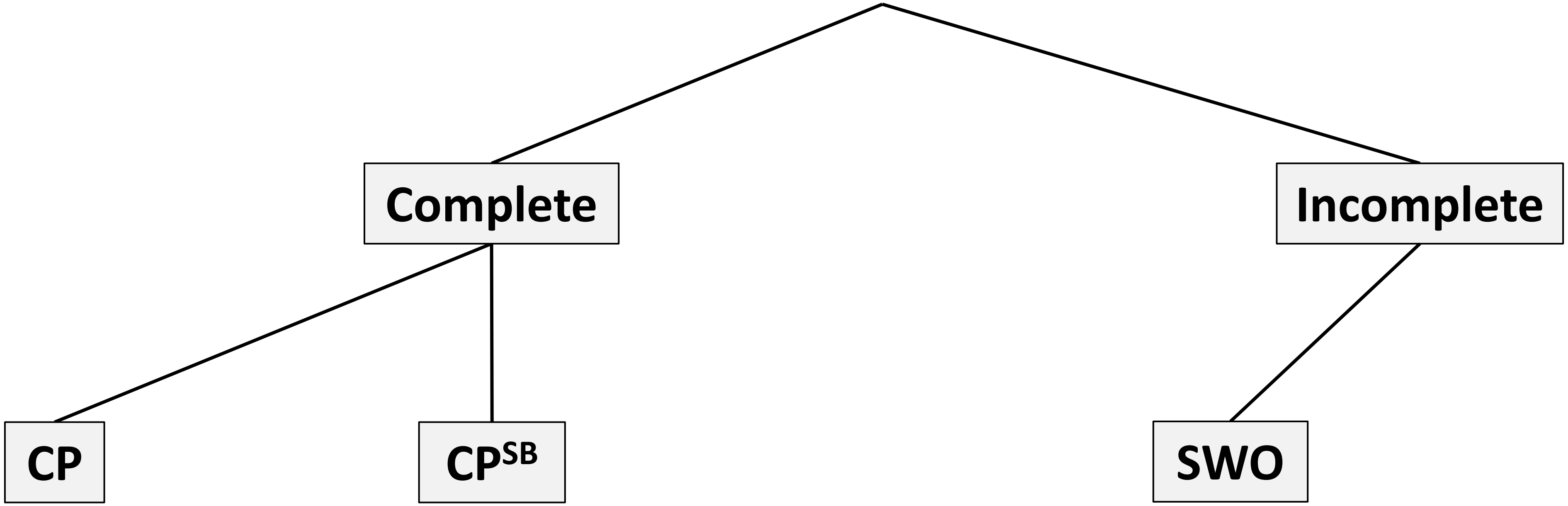
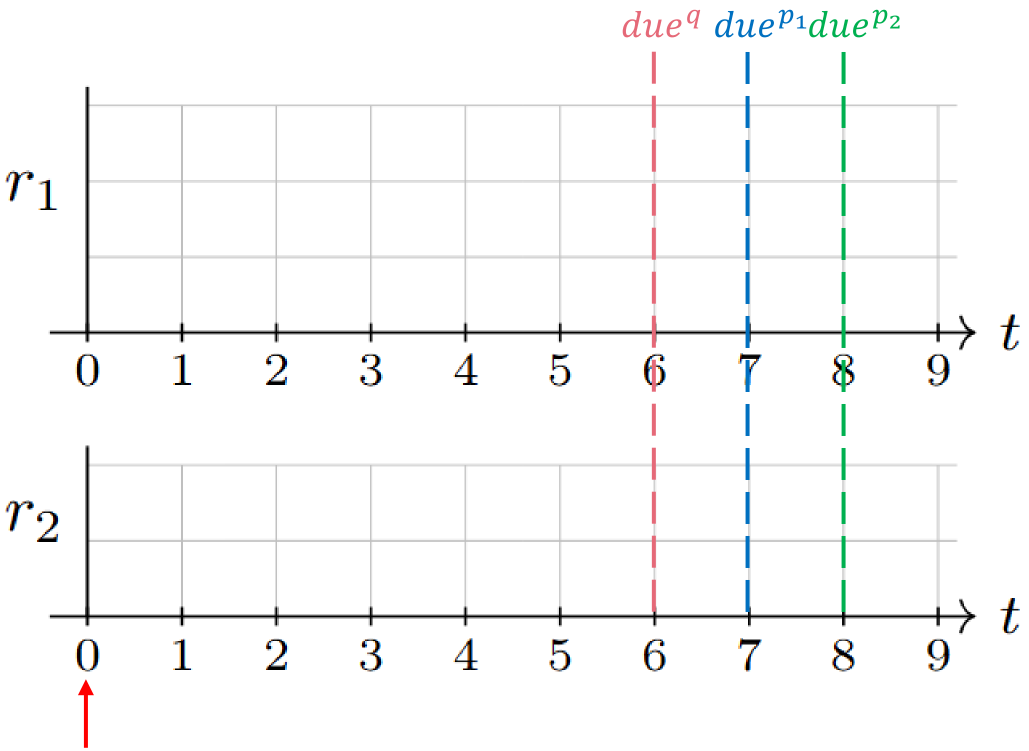


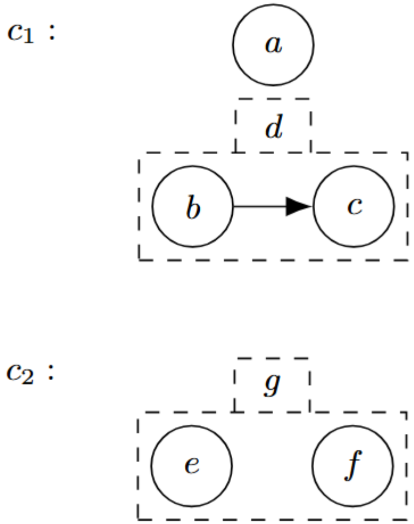
$\boxed{\textbf{CP}}$ **+** $\forall c \in C, \forall p, q \in I_c : p \prec_c q, \forall a \in A_c^{Atom}$ $\quad$ $\text{startBeforeStart}(\mathbf{itv}_{a,p}, \mathbf{itv}_{a,q})$

Solving Approaches



SWO (Greedy Algorithm)





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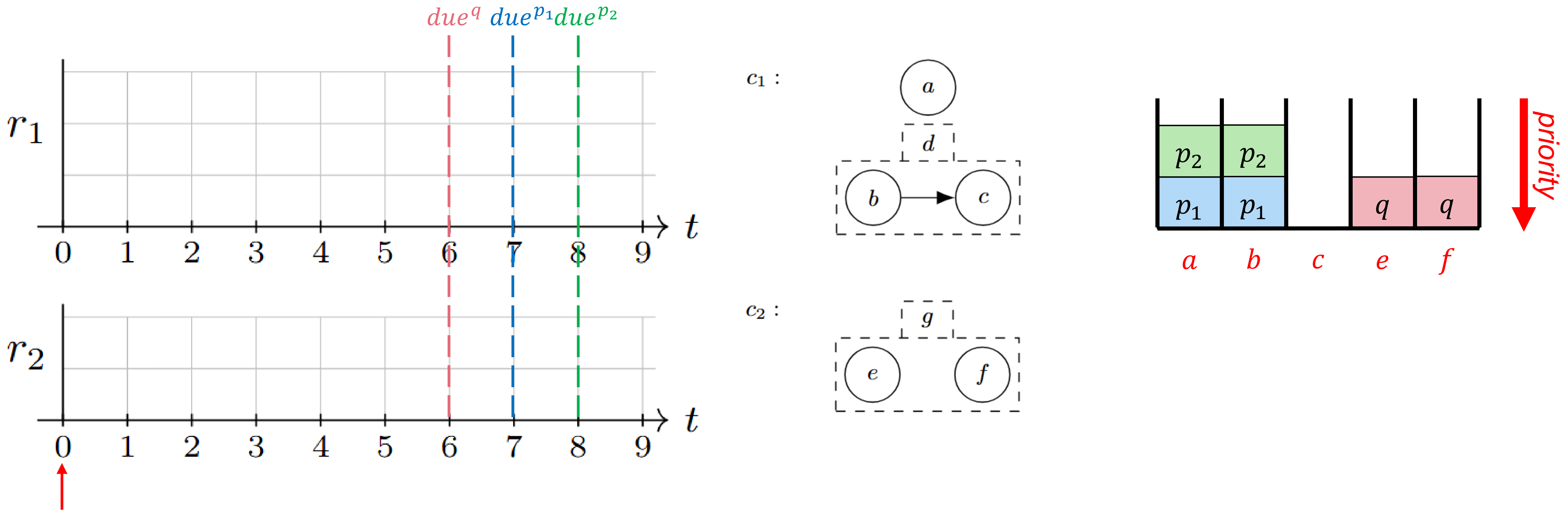
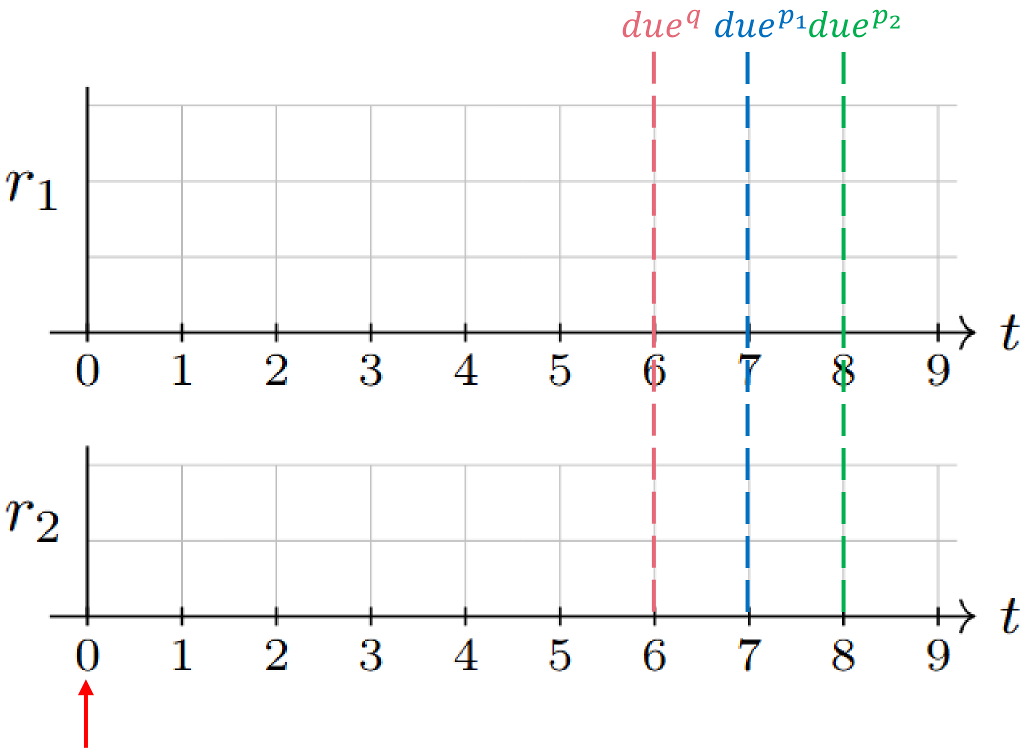
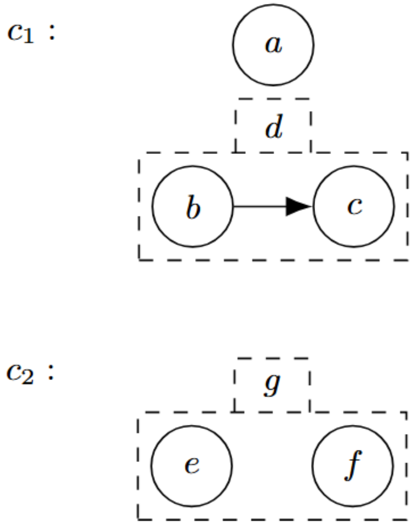
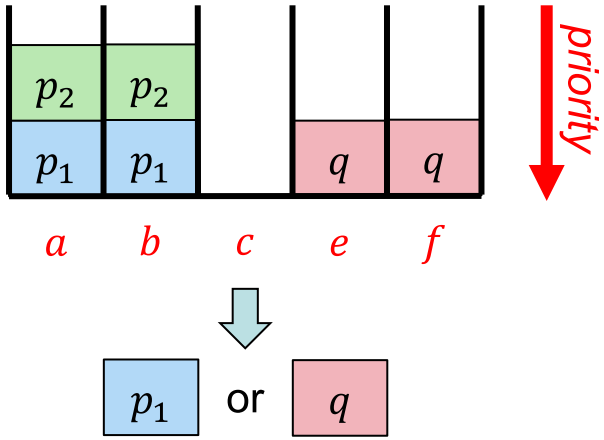


SWO (Greedy Algorithm)







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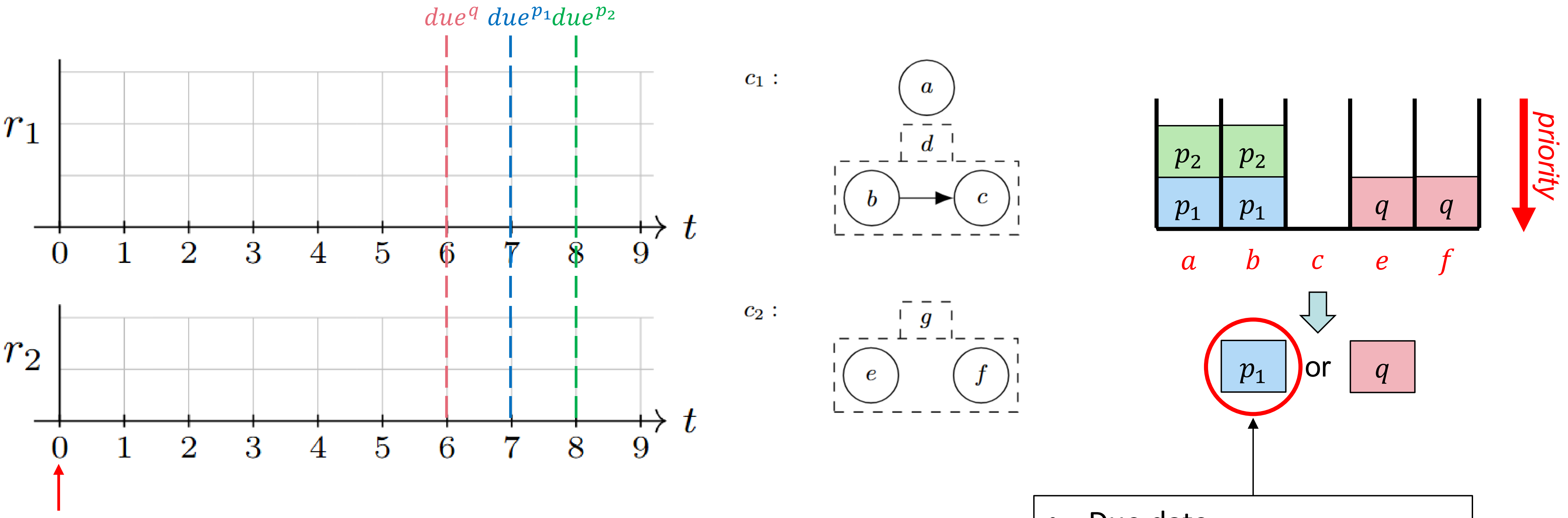
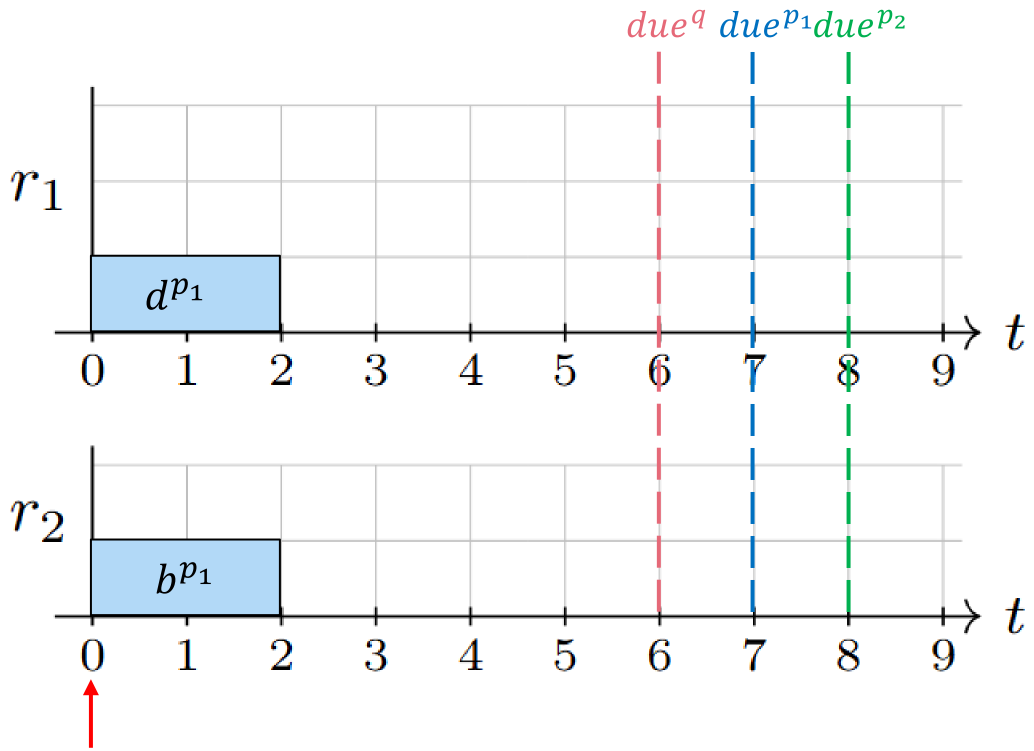
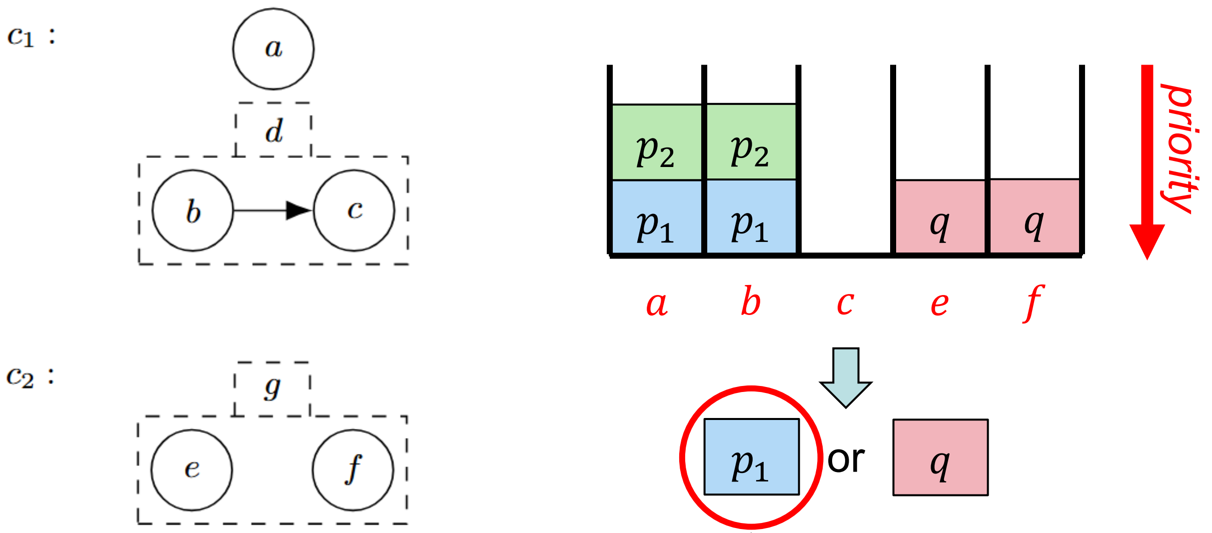


- Due date
- Required time to complete
- Current time moment

SWO (Greedy Algorithm)





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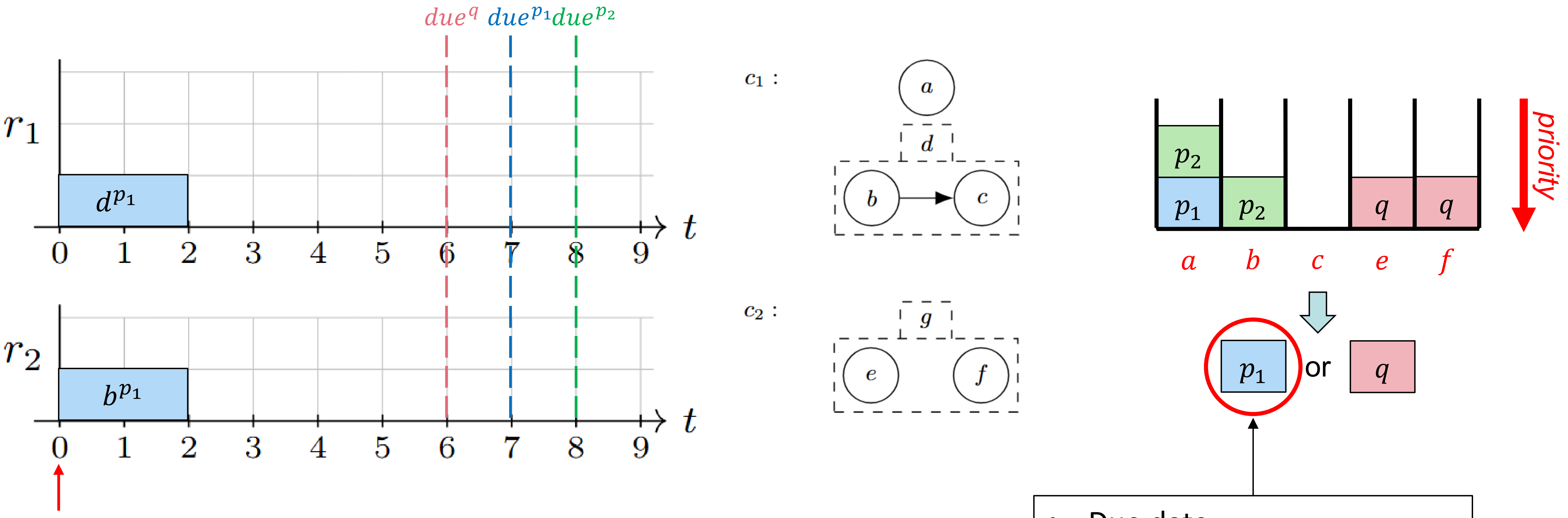

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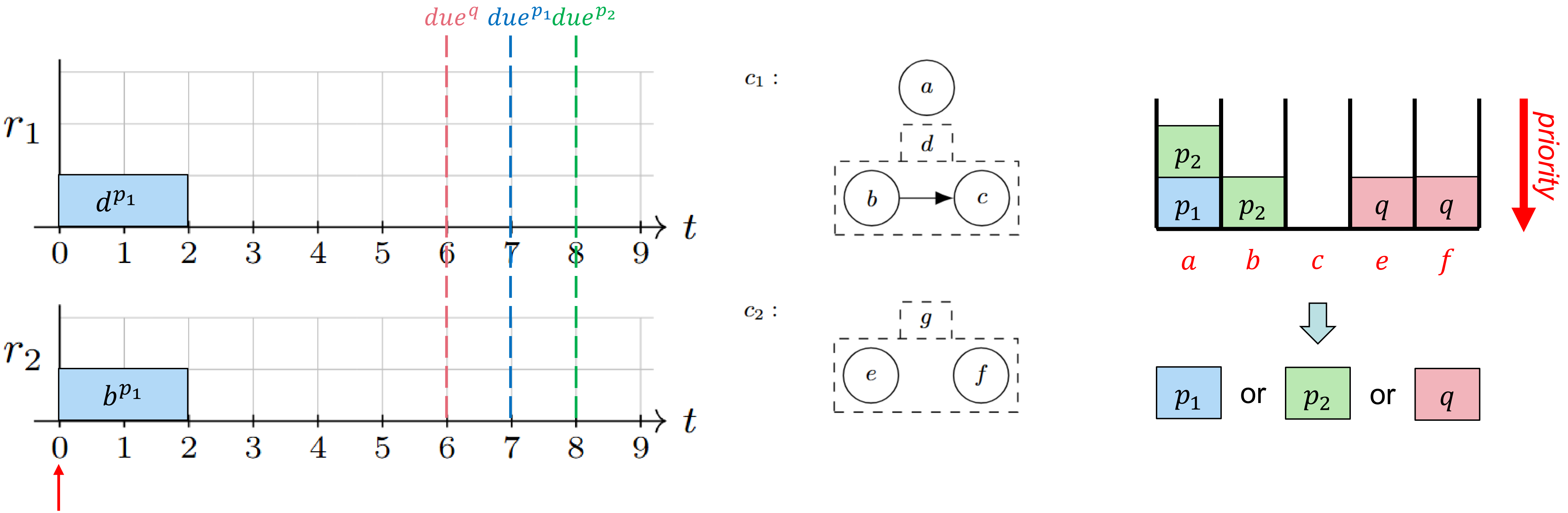

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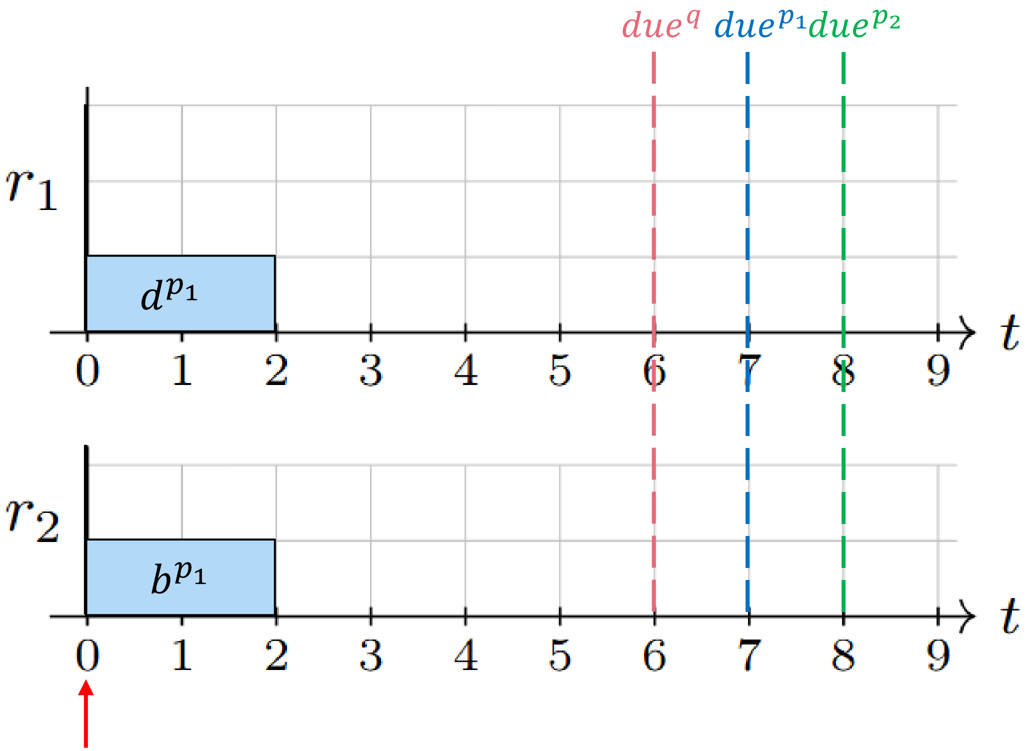

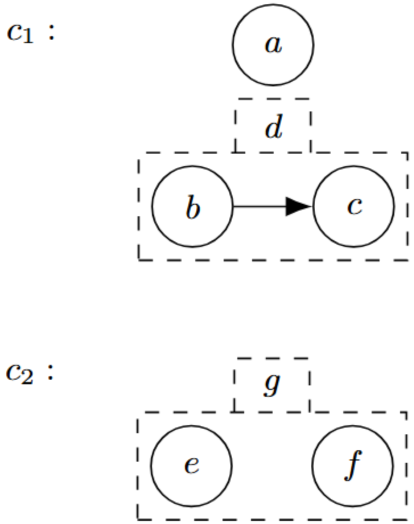

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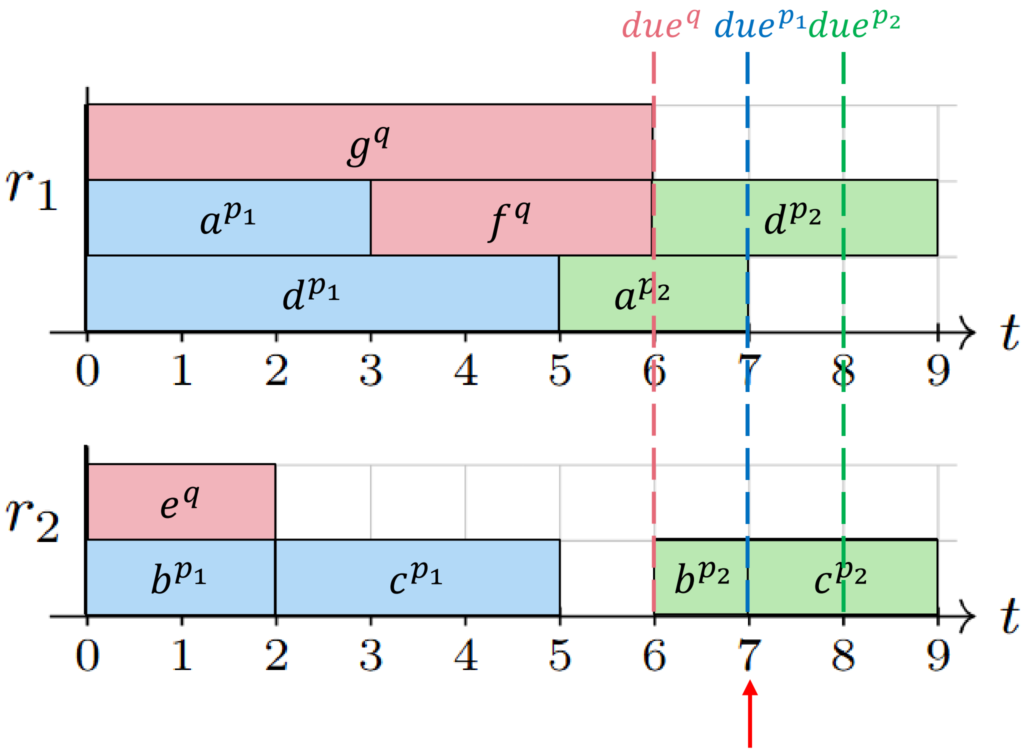

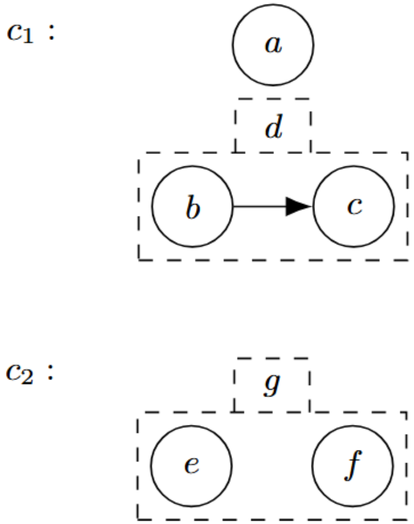

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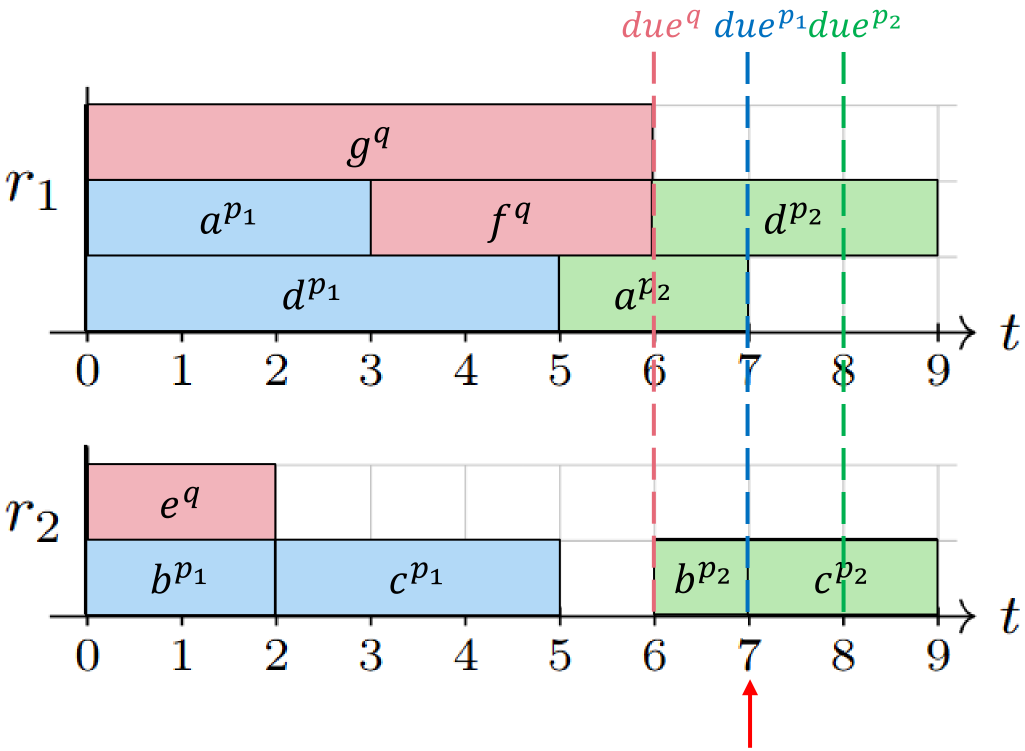

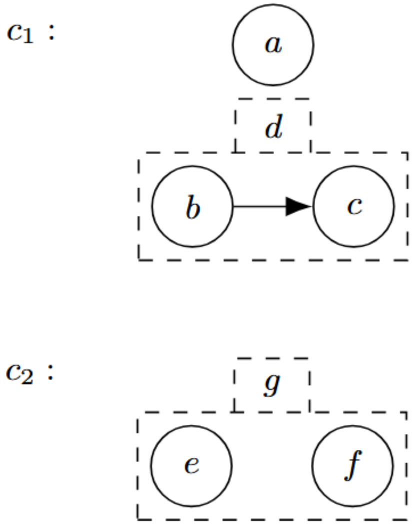

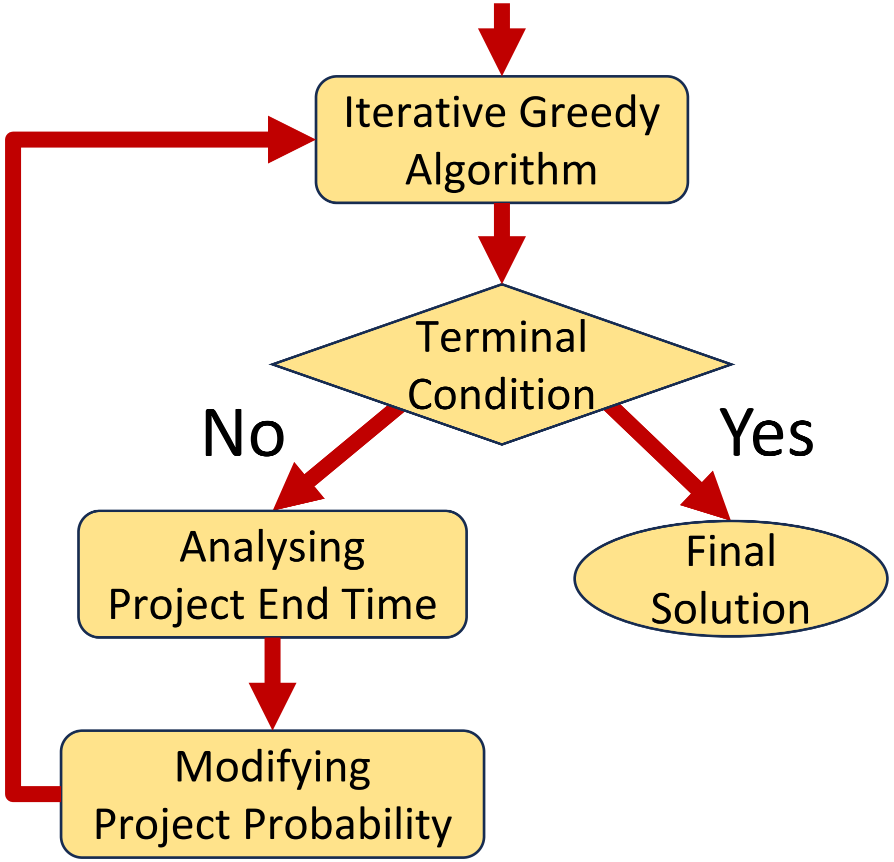

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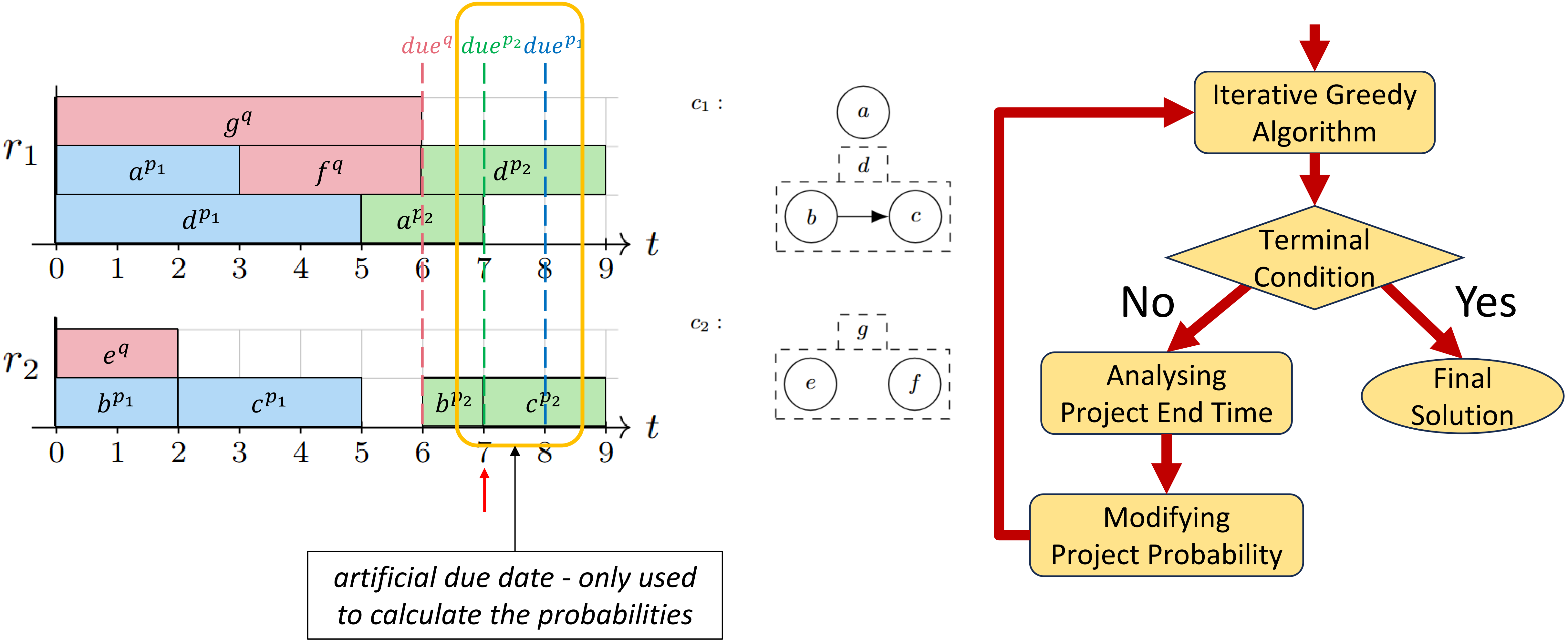
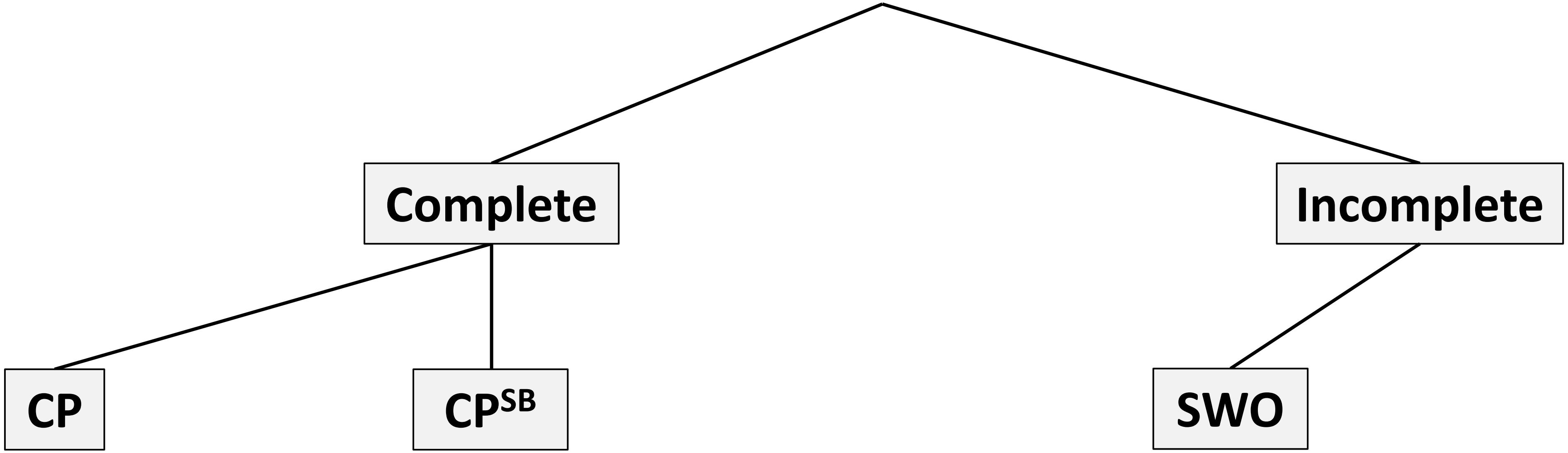


Solving Approaches



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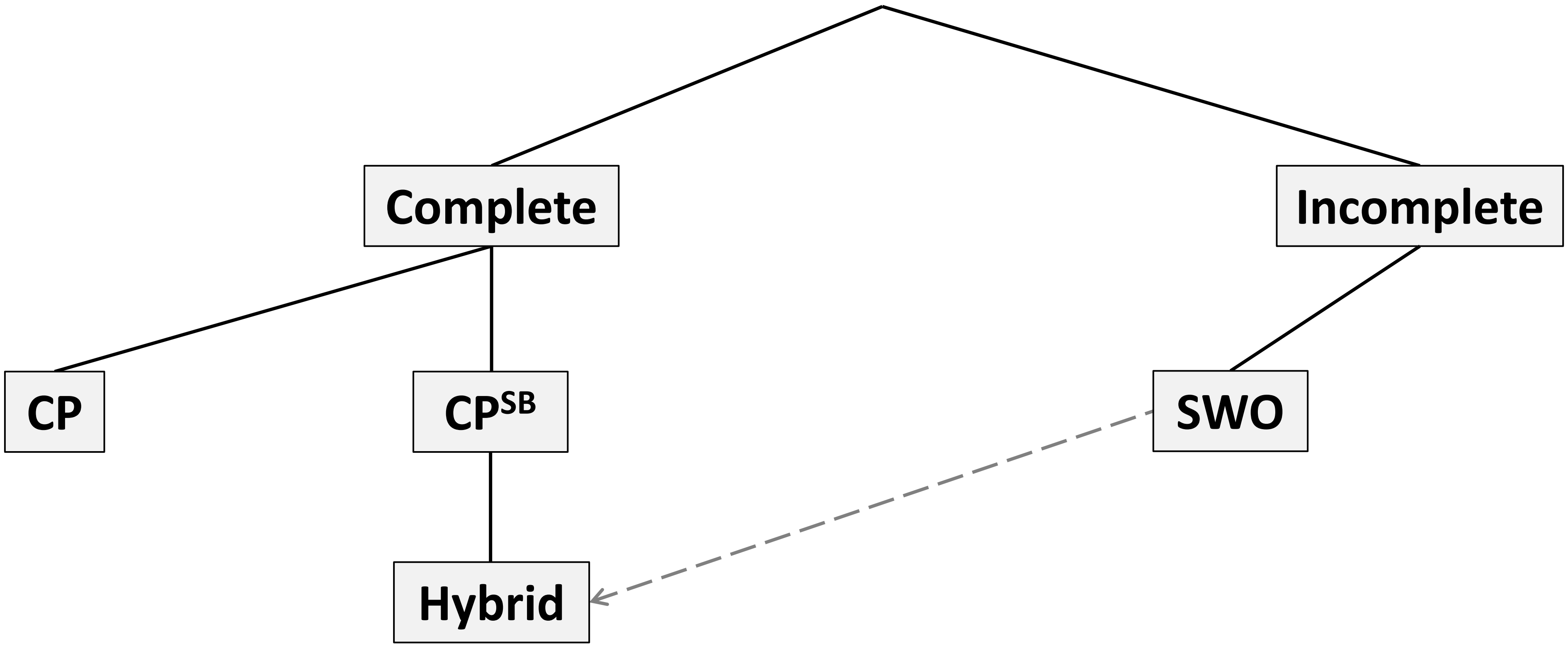

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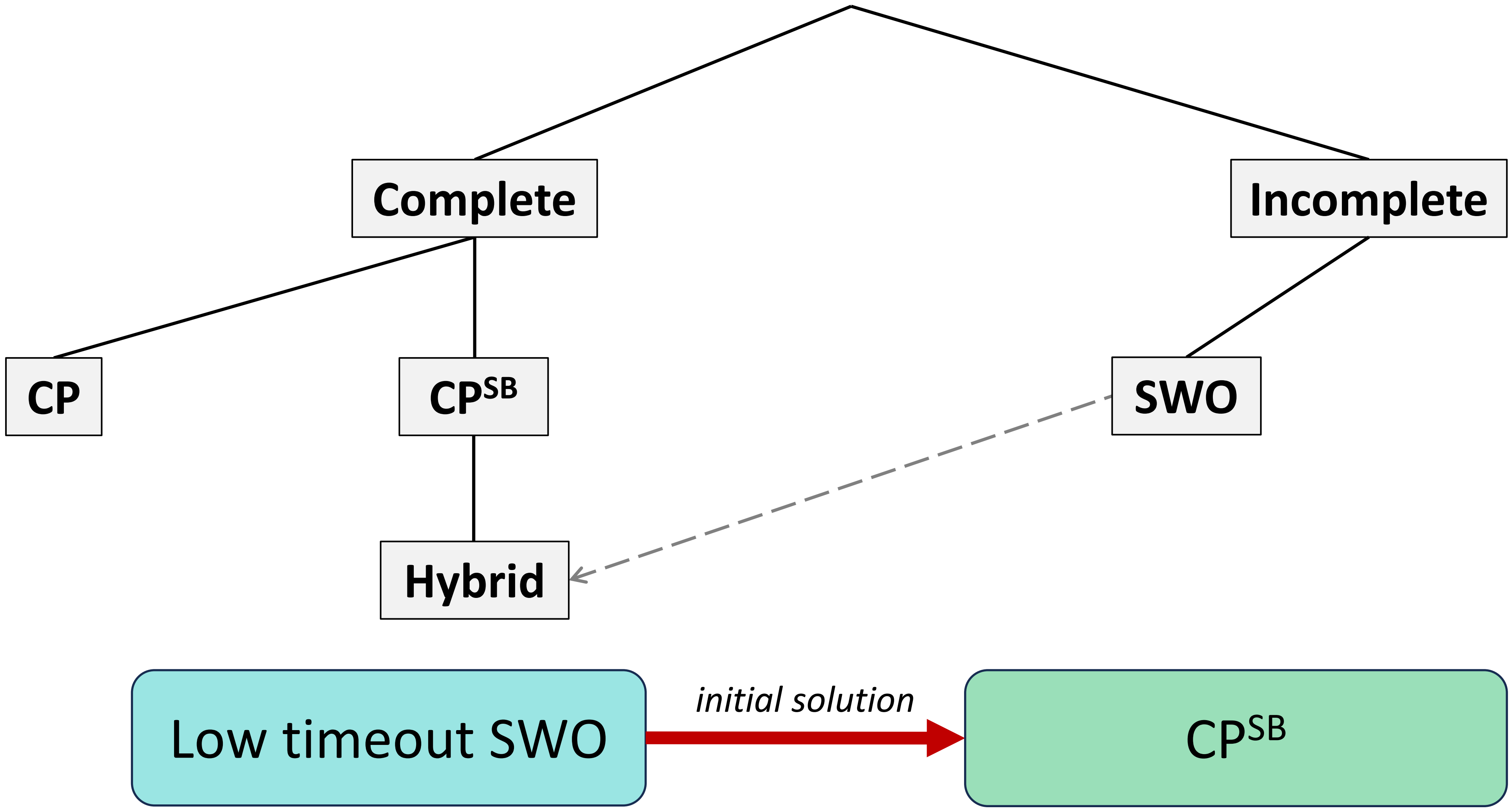

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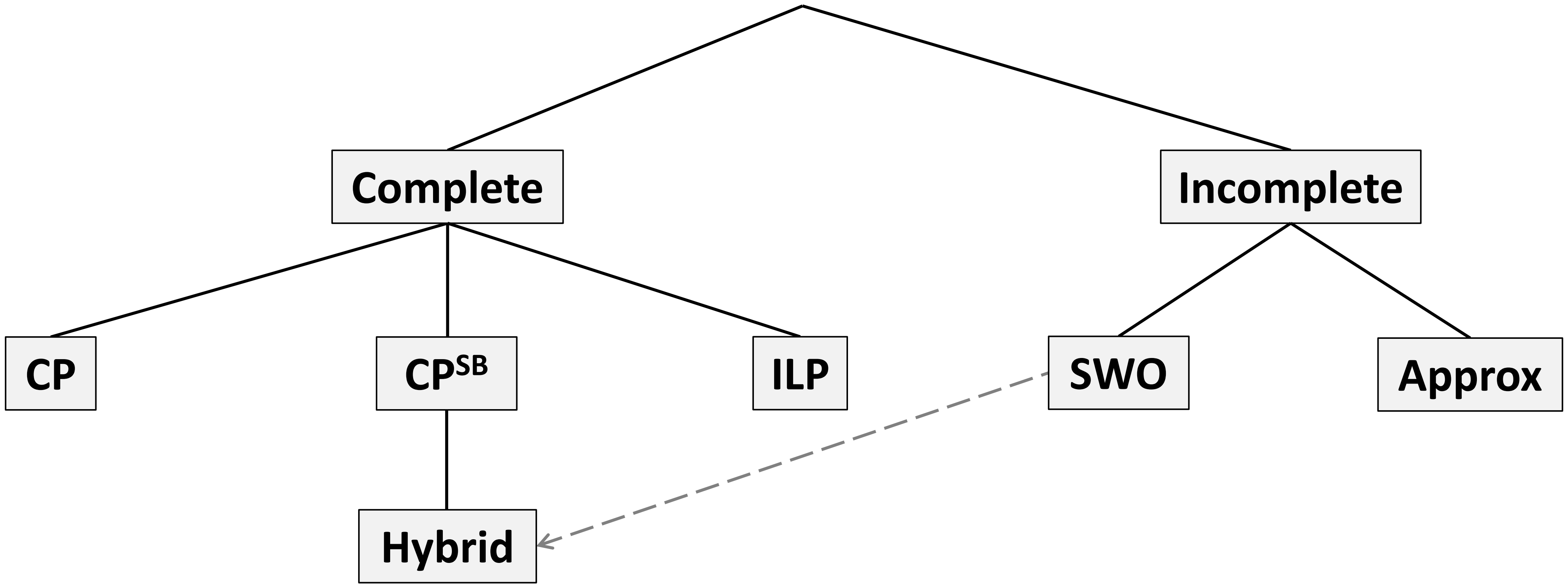

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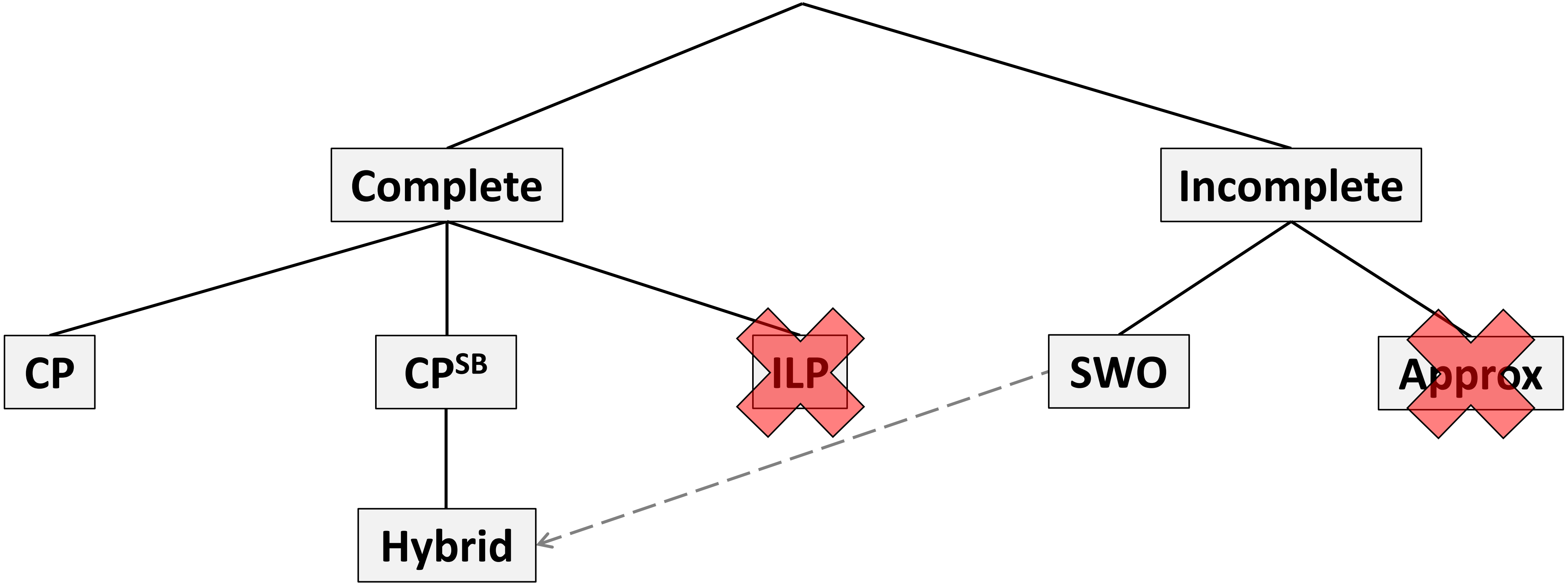

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Learning Curve

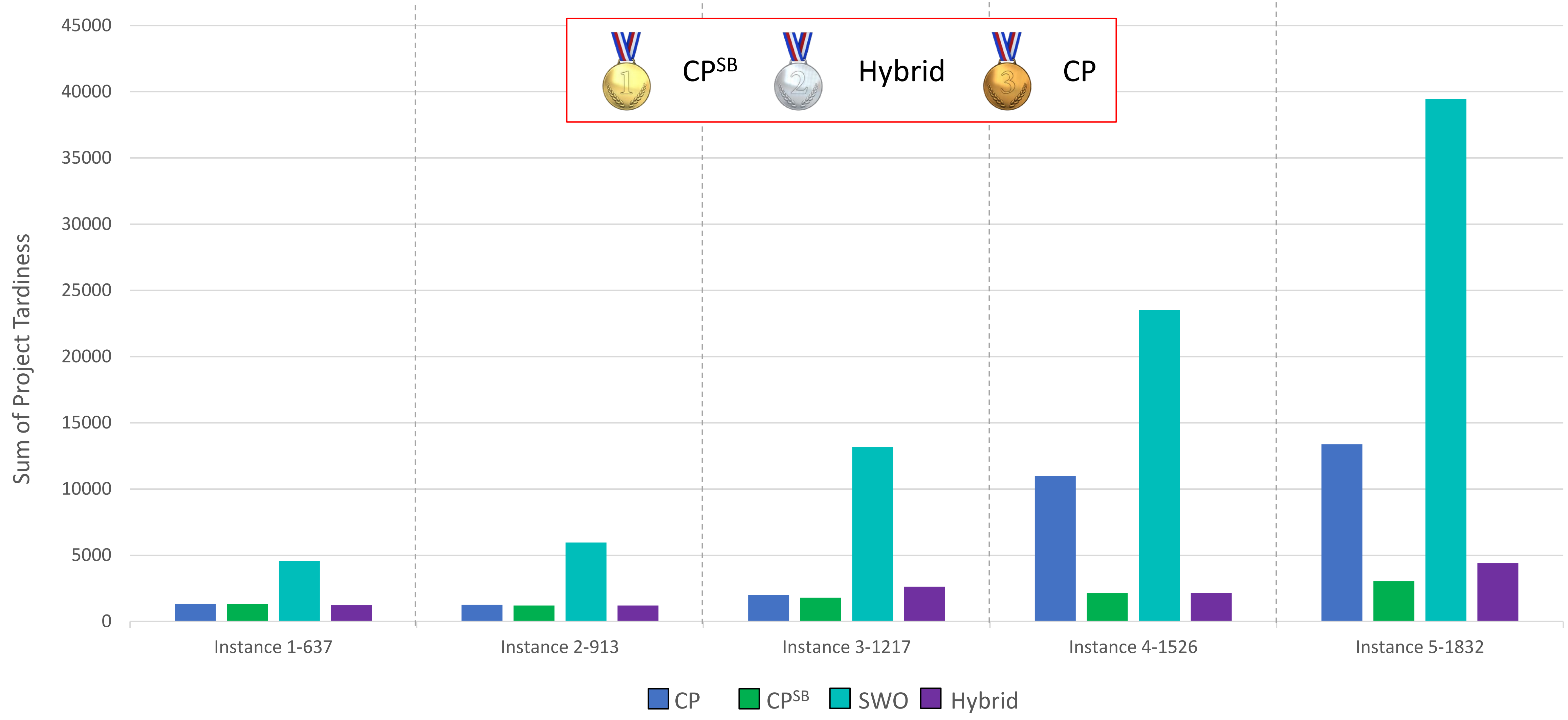
- $\forall n \in \mathbb{N}, \quad dur_a(n) = dur_a^\infty + \left\lceil (dur_a^0 - dur_a^\infty) * (n+1)^{\log_2 l} \right\rceil$

Industrial Benchmarks

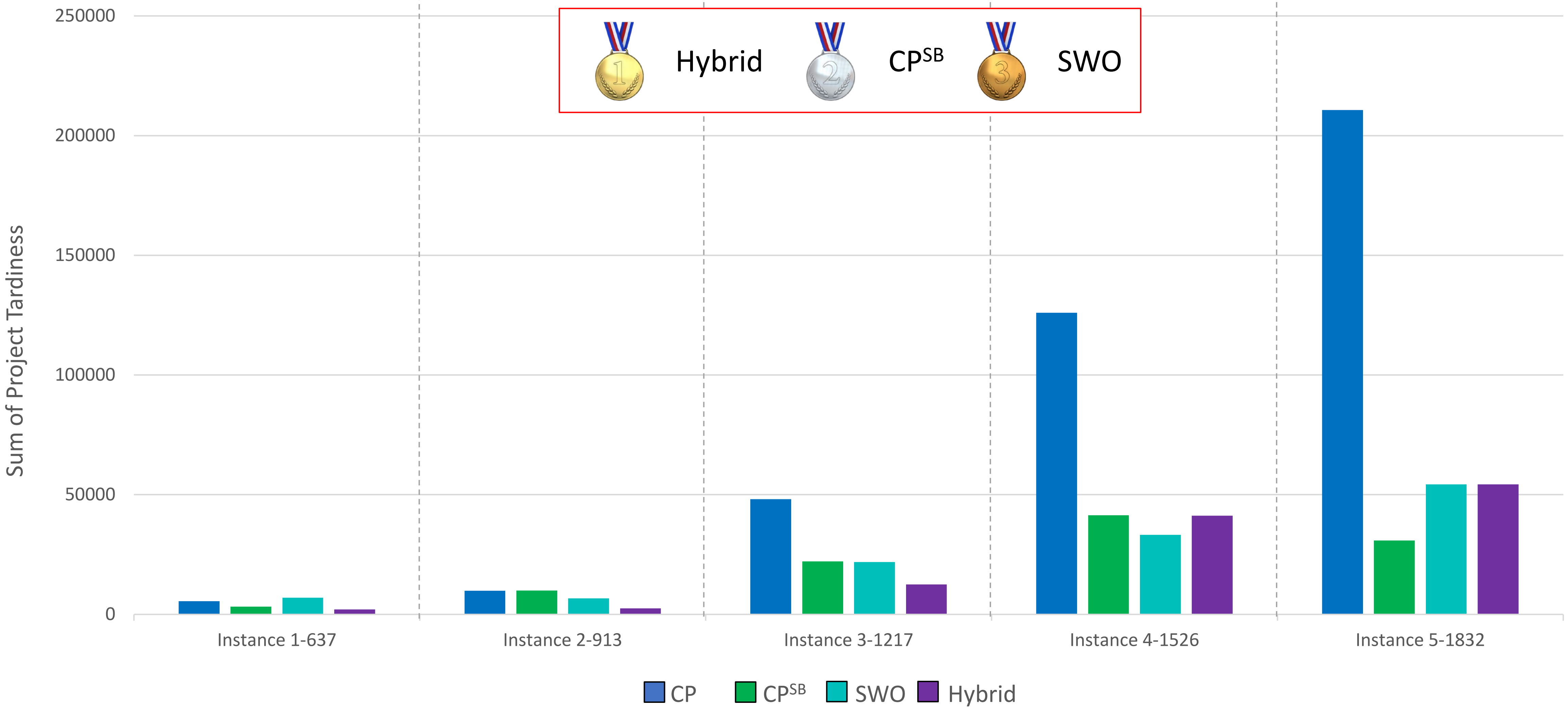
Instances		$\lvert C \rvert$	$\lvert A_c \rvert$	$\lvert A_c^{Comp} \rvert$	$\lvert I_c \rvert$	$\lvert R \rvert$	$\lvert capa_r \rvert$	l
Satellite	Original	3	≤ 30	≤ 3	≤ 5	40	≤ 16	$[0.05,0.95]$
	Extended	6			≤ 14			0.85

Test environment:
- IBM CP Optimizer 22.1.1 / Julia 1.10.1
- Timeout: 2h / 15s

Industrial Benchmarks (2h)



Industrial Benchmarks (15s)



PSP-based Benchmarks

1 class = 1 RCPSP from PSPLIB

- Several classes
- Multiplicity projects
- Random due dates
- Random learning rate
- Resource capacities = sum of PSPLIB resource capacities

Instances		$\lvert C\rvert$	$\lvert A_c\rvert$	$\lvert A_c^{Comp}\rvert$	$\lvert I_c\rvert$	$\lvert R\rvert$	$\lvert capa_r\rvert$	l
PSP-based	Small	$[\![2,4]\!]$	$\{30,60\}$	0	$[\![5,10]\!]$	4	$\sum_{i_{LIB}} capa_r^{i_{LIB}}$	$[0.45,0.95]$
	Large	$[\![5,7]\!]$	$\{60,90,120\}$					

PSP-based Benchmarks

- 50 instances
- Dataset available online

Timeout	Dataset	CP	CP^{SB}	SWO	Hybrid
2h	Small	21	21	0	21
	Large	17	16	0	16
15s	Small	22	16	0	19
	Large	15	4	6	3

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V. Conclusion

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✓CP-based approaches showed the best performance in tests

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- ✓Learning effect is important in HM-RCPSP
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- ➢Explore another potential metaheuristic

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- ✓ CP-based approaches showed the best performance in tests

- ➢ Explore another potential metaheuristic
- ➢ Dominance breaking variations

V. Conclusion

✓Learning effect is important in HM-RCPSP

✓CP-based approaches showed the best performance in tests

➢Explore another potential metaheuristic

➢Dominance breaking variations

➢Learning effect on similar activities between classes

V. Conclusion

- ✓ Learning effect is important in HM-RCPSP
- ✓ CP-based approaches showed the best performance in tests

- ➢ Explore another potential metaheuristic
- ➢ Dominance breaking variations
- ➢ Learning effect on similar activities between classes
- ➢ Uncertainty learning duration

Thank you for listening!