Implication learning for train dispatching

Bjørnar Luteberget, Giorgio Sartor,
Carlo Mannino

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FP5 TRANS4M-R

Transforming Europe's Rail Freight

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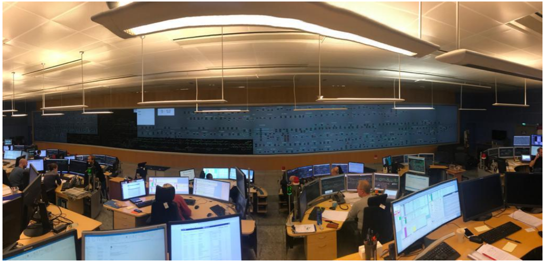
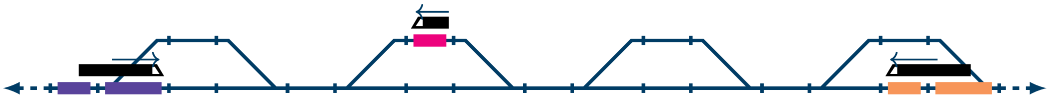
Timetabling and real-time dispatching

A timetable at Oslo central



Dispatchers at Oslo control centre

The train dispatching problem

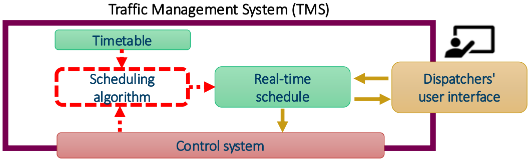


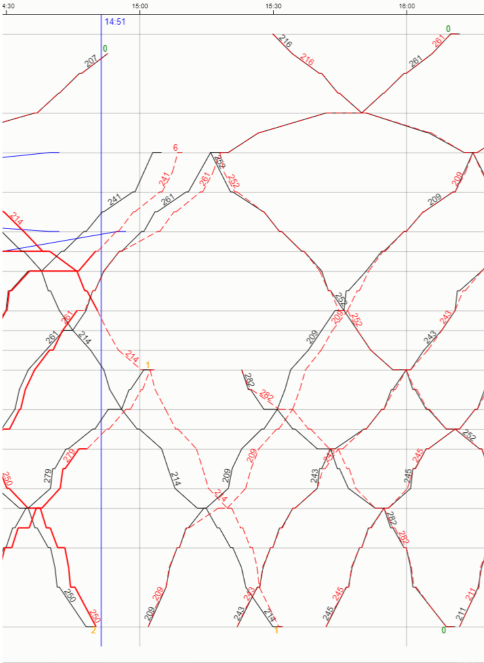
The **train dispatching problem**: given the current position of the trains, decide a **route** and a **schedule** for each train, s.t.:

- … trains do not use the same track segments at the same time, and
- … delays (compared to the timetable) are minimized.

Real-time application

- **Optimized Train Scheduling** can increase throughput and reduce delays.
- Yet, it is still the missing piece of many TMS systems
- That is because it requires state-of-the-art optimization methods, advanced software engineering skills, and a tremendous amount of experience





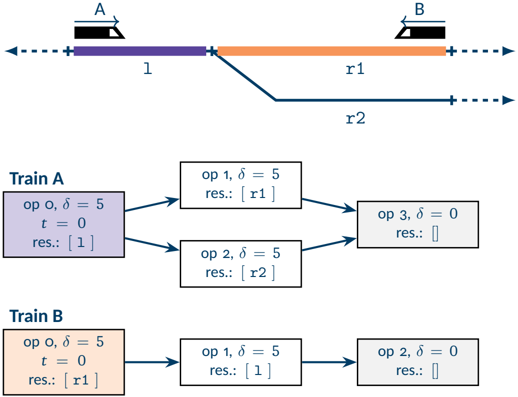
Real-time train dispatching is difficult!

It is very hard to solve train dispatching problems in practice:

1. The core is a **job-shop scheduling problem** (NP-hard) (Mascis & Pacciarelli 2002)
2. In practice, additional rules and constraints.
3. Very large instances (of practical interest)
4. Short computational time ($<$ 2 minutes)

Formalizing the train dispatching problem

- A train is a directed acyclic graph of **operations**.
- A **route** for a train is a path through the graph from an initial to a final node.
- A **schedule** is an assignment of start times to each operation in the route.
- Each operation requires exclusive access to some **resources**.
- **Operations** have start time and duration bounds.



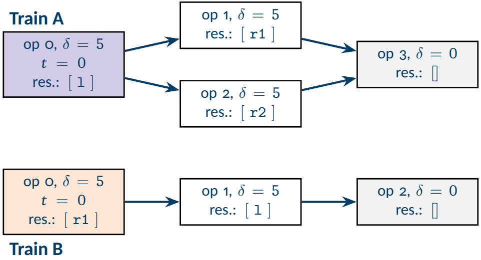
State of the art

Approaches to solving train dispatching problems:

- Alternative graph (AG) models (**“precedence disjunctions”**)
  - Create graph with all potential precedence constraints between conflicting operations and select a subset of precedence constraints.
  - MILP with many big-M constraints (custom branch-and-bound beneficial)
- Time-indexed models (**“discretized time-space packing”**)
  - Decide on a set of discrete time ”slots” and allow only one train in each location in each time slot.
  - MILP with packing constraints (column generation typically beneficial)
- Heuristics
- Spatial and temporal decomposition is also very important (but out of scope here)

Alternative graph models

- Let $x_j^i \in \{0, 1\}$ be the decision of whether train i **performs** operation j.
- x must be a path in the graph.
- Let $t_j^i, t^{*i}_j \in \mathbb{R}$ be the **start and end time** of train i's operation j. (End time must be start time of the next operation.)



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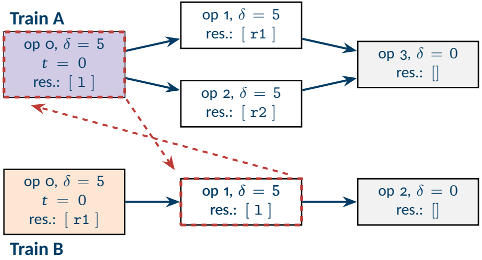
- Let $t^i_j, t^{*i}_j \in \mathbb{R}$ be the **start and end time** of train i's operation j. (End time must be start time of the next operation.)
- For pair of conflicting operations x^i_j, x^k_l:

$$(x^i_j = 0) \lor (x^k_l = 0) \lor (t^{*i}_j \le t^k_l) \lor (t^{*k}_l \le t^i_j)$$



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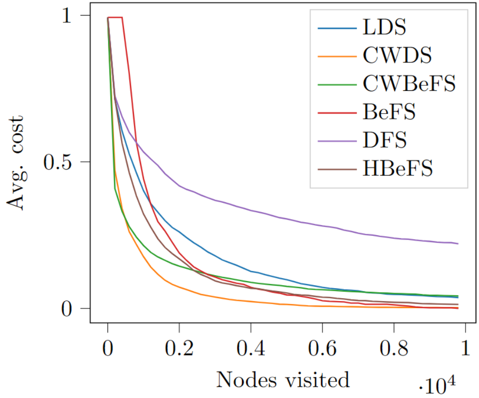
Alternative graph

$$(x^i_j = 0) \lor (x^k_l = 0) \lor (t^{*i}_{\ j} \leq t^k_l) \lor (t^{*k}_{\ l} \leq t^i_j)$$

- Introduce variables y for selecting the last two disjuncts.
- The disjunctive constraint can be linearized with big-M.
- Branch-and-bound over decisions x and y.
- Node relaxations optimize timing t as a longest path problem (easy).
- Called **"alternative graph"** because the relaxation is a project scheduling graph and the branch-and-bound selects between alternative choices of precedences.

Diving heuristics



- Exact optimality can be found using best-bound-first tree search.
- Diving heuristics seem very effective when routing is “easy”.

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Alternative graph

- Introduced without routing in 2002.
  (Mascis & Pacciarelli, 2002)
- Underlies many of the best real-time dispatching algorithms, with extensions to routing and spatial decomposition.
  (D'Ariano et al., 2007), (Pellegrini et al., 2015), (Lamorgese & Mannino, 2015), (Leutwiler & Corman 2022)
- Reasonably scalable **when routing is very limited** (or decomposable).

- With comprehensive routing choices: multiple independent decisions to make before the node relaxation's bound increases.

$$(x^i_j = 0) \vee (x^k_l = 0) \vee (t^{*i}_j \leq t^k_l) \vee (t^{*k}_l \leq t^i_j)$$

Exact methods for routing+scheduling

- **Without routing**: branch-and-bound (and MILP) is effective.

  (D'Ariano et al. 2006)

- With **"little"** routing, e.g. simple stations: Logic Benders decomposition turns routing into scheduling disjunctions.

  (Lamorgese et al. 2015, Leutwiler et al. 2023)

- **"Wide"** instances, e.g. short infrastructure and/or time horizon: time-indexed formulations, heuristically limited routing, fully enumerated routings.

  (Reynolds et al. 2020, Pellegrini et al. 2014, Samà 2015, Croella et al. 2025)

- **Much routing**, both wide and long: routing local search + exact scheduling, etc.

  (Corman et al. 2010, Samà 2015)

Deadlock detection

- In passenger traffic: routes and schedules have been planned in advance, so it is often easy to find a feasible solution.
- In American freight traffic: not necessarily any detailed timetable.
- It can be hard to determine whether there is **any solution at all!**
- Specialized deadlock detection models disregard **scheduling objectives** and **(physical) time**.
- Literature: transition system models (Dal Sasso et al., 2021) alternative graph models (Dal Sasso et al. 2025)

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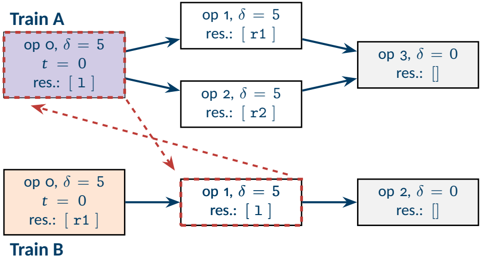
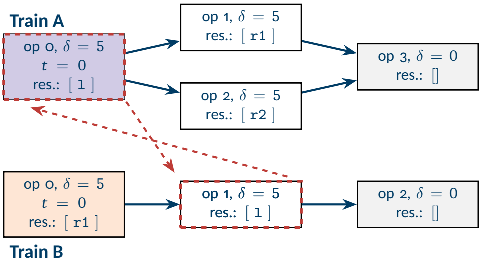
Cycles formulation for deadlocks (Dal Sasso et al. 2023)



Cycles formulation for deadlocks (Dal Sasso et al. 2023)

- Routing variables x and flow conservation

$$\sum_{i \in \delta^+(a)} x_i - \sum_{i \in \delta^-(a)} x_i = b_a$$



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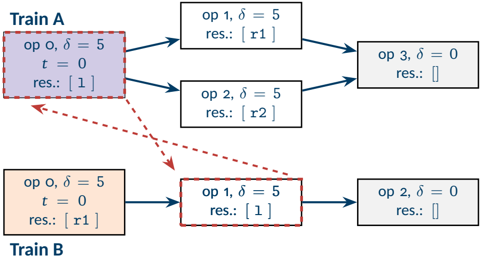
- Precedence variables y for operations with overlapping resources:

$$y_{ab} + y_{ba} = 1$$



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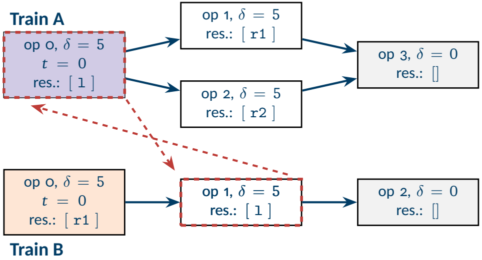
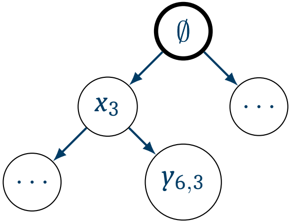
- Cycle elimination constraints

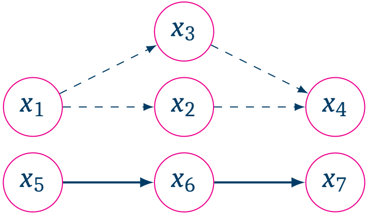
$$\sum_{i \in R(C)} x_i + \sum_{(a,b) \in P(C)} y_{ab} \leq |R(C)| + |P(C)| - 1$$



Generating cycle constraints

- The cycles formulation is exponential – efficient row generation is essential.
- How do we actually detect the cycles? Incremental cycle detection algorithm





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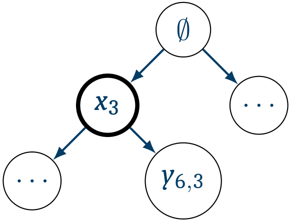

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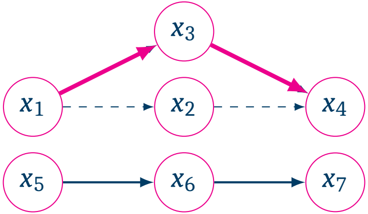

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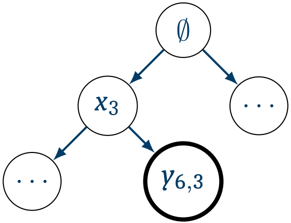
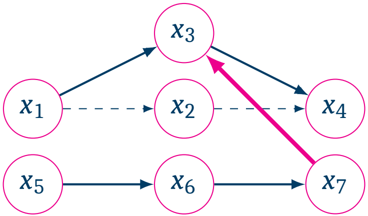
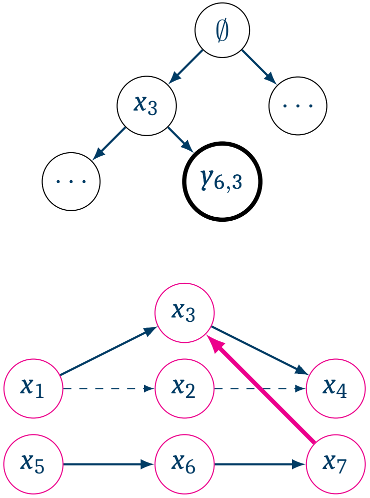




Generating cycle constraints

- The cycles formulation is exponential – efficient row generation is essential.
- How do we actually detect the cycles? Incremental cycle detection algorithm
- With incremental longest path instead, This is actually scheduling.



Cycle elim./disjunctive constraints/clauses/implications

- Disjunctive binary assignment constraints are also called clauses

$$x_1 \vee x_2 \vee \neg x_3$$

$$(x_1 = 1) \vee (x_2 = 1) \vee (x_3 = 0)$$

- They are also linear constraints (over binary variables)

$$x_1 + x_2 + (1 - x_3) \geq 1$$

- We get domain propagation (implied assignment) when all but one alternative is false

$$((x_1 = 0) \wedge (x_3 = 1)) \Rightarrow (x_2 = 1)$$

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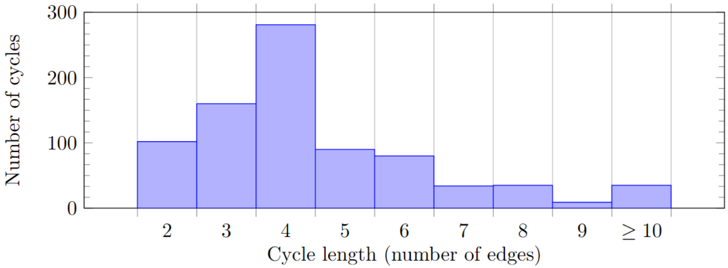
SAT deadlock detection

Instance				MIP ticks (Dal Sasso et al., 2021)		MIP cycles (Dal Sasso et al., 2023)		SAT transition system (Luteberget, 2021)		SMT cycles (unpublished)	
#	Result	n_r	n_t	Steps	Time (s)	Iter.	Time (s)	Steps	Time (s)	Iter.	Time (s)
T11	Dead	62	2	27	17.60	N/A		3	0.00	650	0.01
T12	Dead	62	4	39	>60.00	N/A		10	0.10	2217	0.07
T13	Dead	62	4	39	>60.00	N/A		10	0.01	1262	0.04
T14	Live	62	4	39	3.27	N/A		6	0.00	103	0.04
T15	Dead	46	4	42	>60.00	N/A		6	0.01	48	0.00
T16	Live	62	5	50	5.33	N/A		5	0.01	50	0.00
T17	Live	62	4	50	43.11	N/A		6	0.01	170	0.00
T18	Dead	62	4	50	>60.00	N/A		6	0.02	234	0.00
T19	Dead	62	5	51	>60.00	N/A		6	0.01	132	0.00
T20	Dead	70	5	57	>60.00	N/A		8	0.05	7	0.00
C11	Dead	274	5	114	>60.00	3	0.69	7	0.09	652	0.02
C12	Live	35	5	21	0.08	0	0.02	4	0.00	3	0.00
C13	Dead	257	6	68	0.48	0	0.13	8	0.77	1	0.00
C14	Live	317	6	77	1.79	3	1.19	4	0.01	26	0.01
C15	Dead	102	6	32	0.20	0	0.05	7	0.02	18	0.00
C16	Live	142	6	34	0.54	0	0.16	4	0.00	14	0.00
C17	Live	137	6	70	1.86	3	0.24	6	0.01	71	0.00
C18	Live	325	7	54	3.46	0	6.35	5	0.08	38	0.06
C19	Live	219	9	108	4.50	29	10.90	7	0.02	117	0.01
C20	Live	837	9	194	14.73	1	3.93	4	0.07	378	0.09

Implication learning from scheduling cycles

- In the pure-scheduling instances, cycles are only very short, most of them 2 edges (which can be avoided using look-ahead).
- In deadlock detection instances, more varied cycle lengths.



Resolution

$$\frac{A \lor x \qquad B \lor \neg x}{A \lor B}$$

Implication learning in SAT solvers

- SAT solvers quickly assign variables but ensures that each assignment is **consistent with unit propagation**.
- Then, analyze which decisions caused the conflict by performing **resolution**.
- This makes sure that you can **never find the same** partial assignment (unit propagation will happen before).

(Marques-Silva et al., 2002)

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Start with clauses:

- $c_1 : x_1 \vee x_2 \vee x_3$
- $c_2 : x_1 \vee \neg x_2$
- $c_3 : x_1 \vee \neg x_3$

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Assign $\neg x_1$.

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Assign $\neg x_1$. **Propagate** $\neg x_2, \neg x_3$.

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Assign $\neg x_1$. **Propagate** $\neg x_2, \neg x_3$. **Conflicts** with c_1.

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Conflicts with c_1.
Resolve c_1 and c_2:

$$x_1 \vee x_3$$

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Assign $\neg x_1$. **Propagate** $\neg x_2, \neg x_3$.

Conflicts with c_1.

Resolve c_1 and c_2:

$$x_1 \vee x_3$$

Resolve with c_3:

$c_4 : x_1$

Exact routing+scheduling

Two **observations**:

1. **SAT solvers** can determine deadlocks (and find feasible schedules) much faster than MILP-based solvers.
   … but with **no regard to the objective value**.
2. **Diving heuristics** can be very effective when feasibility is "easy", i.e., no choices are logically wrong.

… can we combine the two?

Idea

Working hypothesis

implication learning (i.e., unit propagation and resolution)
makes diving effective in train routing+scheduling.

Implication graph search

Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$

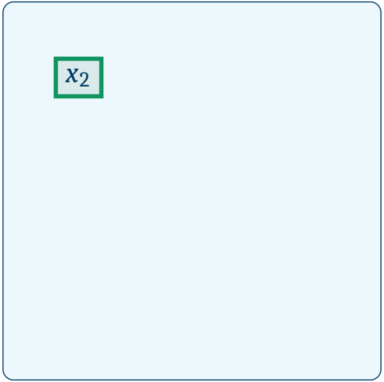
$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$

$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$

$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

Implication graph search



Clauses:

$\neg y_{6,9} \lor \neg y_{9,6}$

$\neg x_2 \lor \neg x_{12} \lor y_{2,12}$

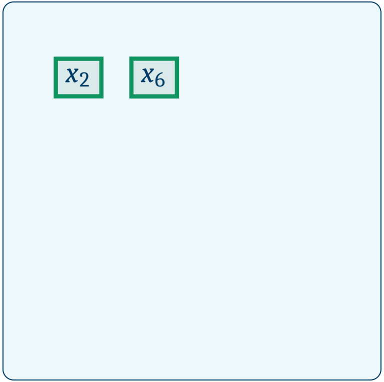
$\neg x_{12} \lor \neg x_8 \lor \neg x_6 \lor \neg y_{8,6}$

$y_{6,9} \lor y_{8,6} \lor \neg x_8$

Loop:

1. Assign a value to variable.

Implication graph search



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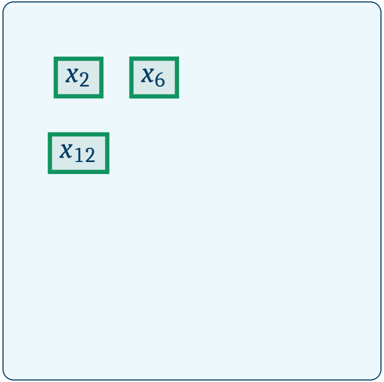

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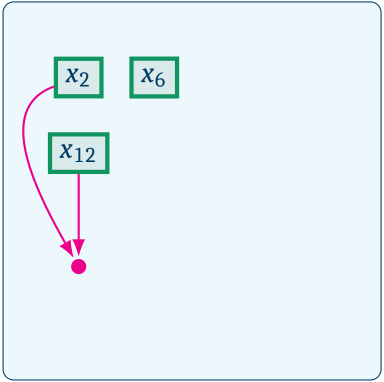

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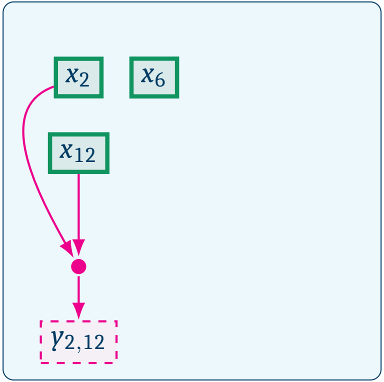
$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.

Implication graph search



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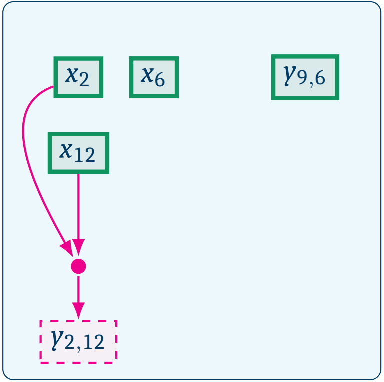


Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$

$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$

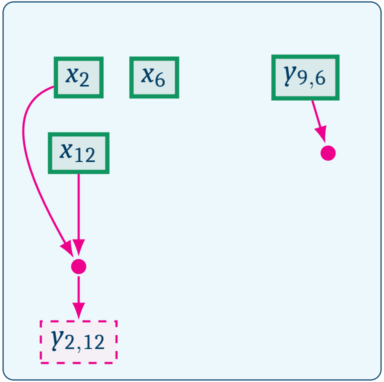
$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$

$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.

Implication graph search



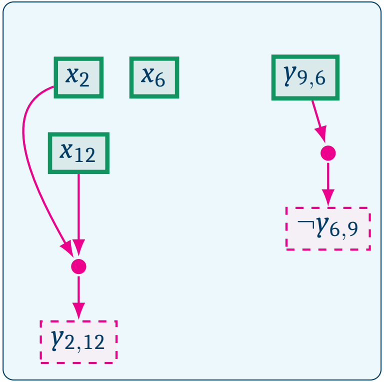
Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$
$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$
$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$
$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.

Implication graph search



Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$
$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$
$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$
$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

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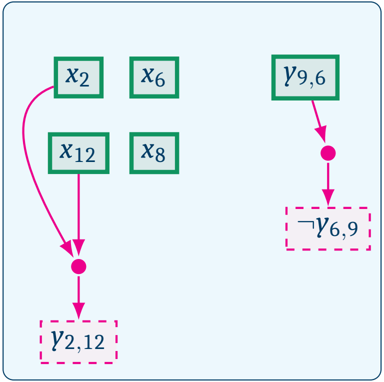
2. Compute unit propagations.

Implication graph search



Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$

$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$

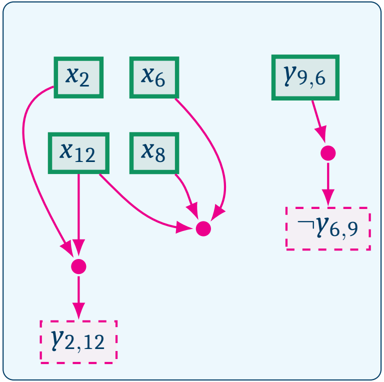
$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$

$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.

Implication graph search



Clauses:

$\neg y_{6,9} \lor \neg y_{9,6}$

$\neg x_2 \lor \neg x_{12} \lor y_{2,12}$

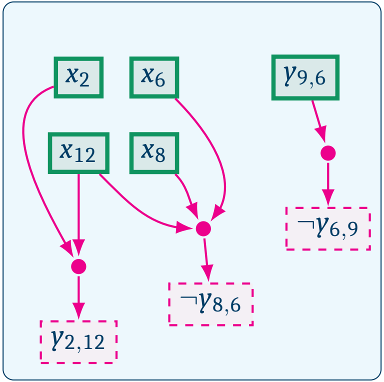
$\neg x_{12} \lor \neg x_8 \lor \neg x_6 \lor \neg y_{8,6}$

$y_{6,9} \lor y_{8,6} \lor \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.

Implication graph search



Clauses:

$\neg y_{6,9} \lor \neg y_{9,6}$

$\neg x_2 \lor \neg x_{12} \lor y_{2,12}$

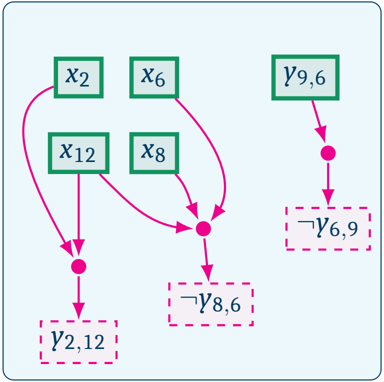
$\neg x_{12} \lor \neg x_8 \lor \neg x_6 \lor \neg y_{8,6}$

$y_{6,9} \lor y_{8,6} \lor \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.

Implication graph search



Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$

$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$

$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$

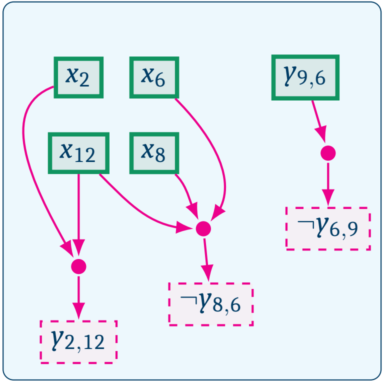
$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.
3. Find violated clause

   $y_{6,9} \vee y_{8,6} \vee \neg x_8$

Implication graph search



Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$

$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$

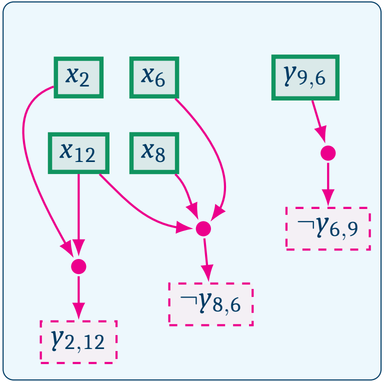
$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$

$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.
3. Find violated clause
   $y_{6,9} \vee y_{8,6} \vee \neg x_8$
4. Resolve to decisions
   $\neg y_{9,6} \vee \neg x_8 \vee \neg x_{12} \vee \neg x_6$

Implication graph search



Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$

$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$

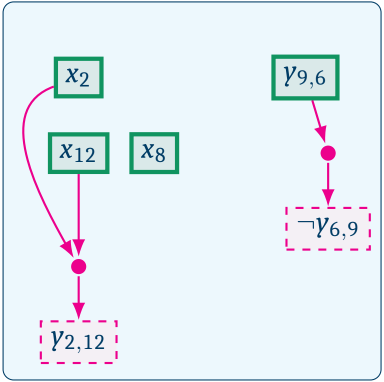
$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$

$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.
3. Find violated clause
   $y_{6,9} \vee y_{8,6} \vee \neg x_8$
4. Resolve to decisions
   $\neg y_{9,6} \vee \neg x_8 \vee \neg x_{12} \vee \neg x_6$
5. Retract any of the decisions.

Implication graph search



Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$

$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$

$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$

$y_{6,9} \vee y_{8,6} \vee \neg x_8$

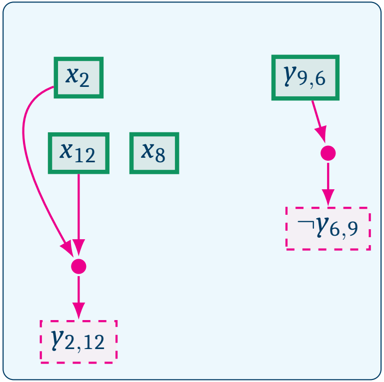
Loop:

1. Assign a value to variable.
2. Compute unit propagations.
3. Find violated clause
   $y_{6,9} \vee y_{8,6} \vee \neg x_8$
4. Resolve to decisions
   $\neg y_{9,6} \vee \neg x_8 \vee \neg x_{12} \vee \neg x_6$
5. Retract any of the decisions.

SINTEF

Europe's Rail FP5 TRANS4M-R Transforming Europe's Rail Freight

Implication graph search



Clauses:

$\neg y_{6,9} \vee \neg y_{9,6}$

$\neg x_2 \vee \neg x_{12} \vee y_{2,12}$

$\neg x_{12} \vee \neg x_8 \vee \neg x_6 \vee \neg y_{8,6}$

$y_{6,9} \vee y_{8,6} \vee \neg x_8$

Loop:

1. Assign a value to variable.
2. Compute unit propagations.
3. Find violated clause
   $y_{6,9} \vee y_{8,6} \vee \neg x_8$
4. Resolve to decisions
   $\neg y_{9,6} \vee \neg x_8 \vee \neg x_{12} \vee \neg x_6$
5. Retract **any** of the decisions.

Exact algorithm! Related to ***resolution search***.
(Chvátal 1997, Hanafi and Glover 2002)

The way ahead

- ✓ Naïve implementation
- ✓ Finds solutions to American freight instances from DISPLIB (`wab_*`).
- … but with no objective or heuristics, objective values are **poor**

- ⏱ Efficient **unit propagation**
- ⏱ Efficient, incremental **scheduling graph** updates
- ⏱ **Heuristic** decisions and retractions based on objective values
- …

Technology for a better society