

\bar{x} \bar{x} \bar{x} CIS1921



Lecture 10: From CP to SAT

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Logisitcs

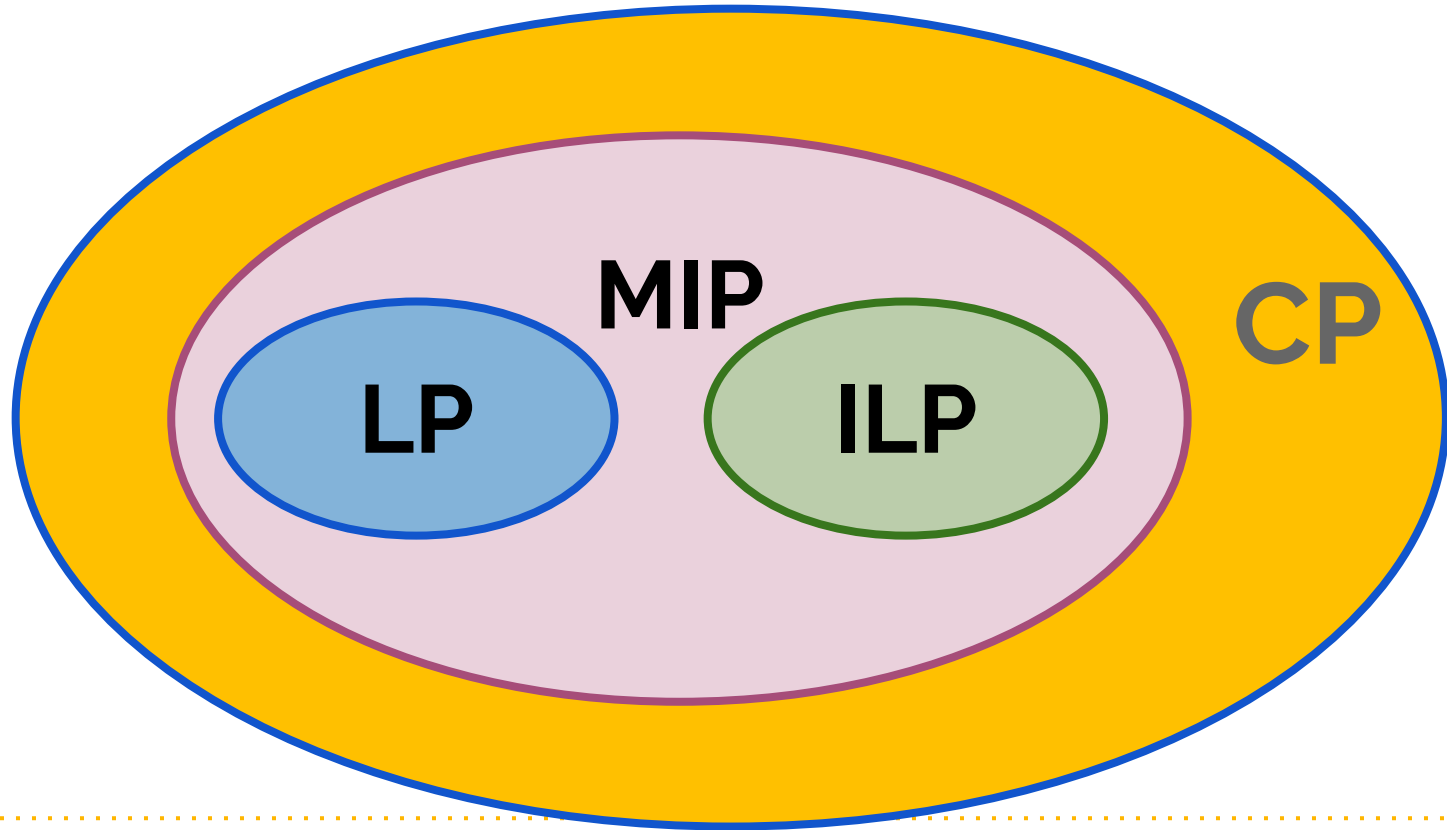
- HW4 update...
- Project:
 - Feedback on proposal released on Gradescope
 - Checkpoint due 11/21 (~75% complete)
 - Please update us on any changes in vision to your project!

Today...

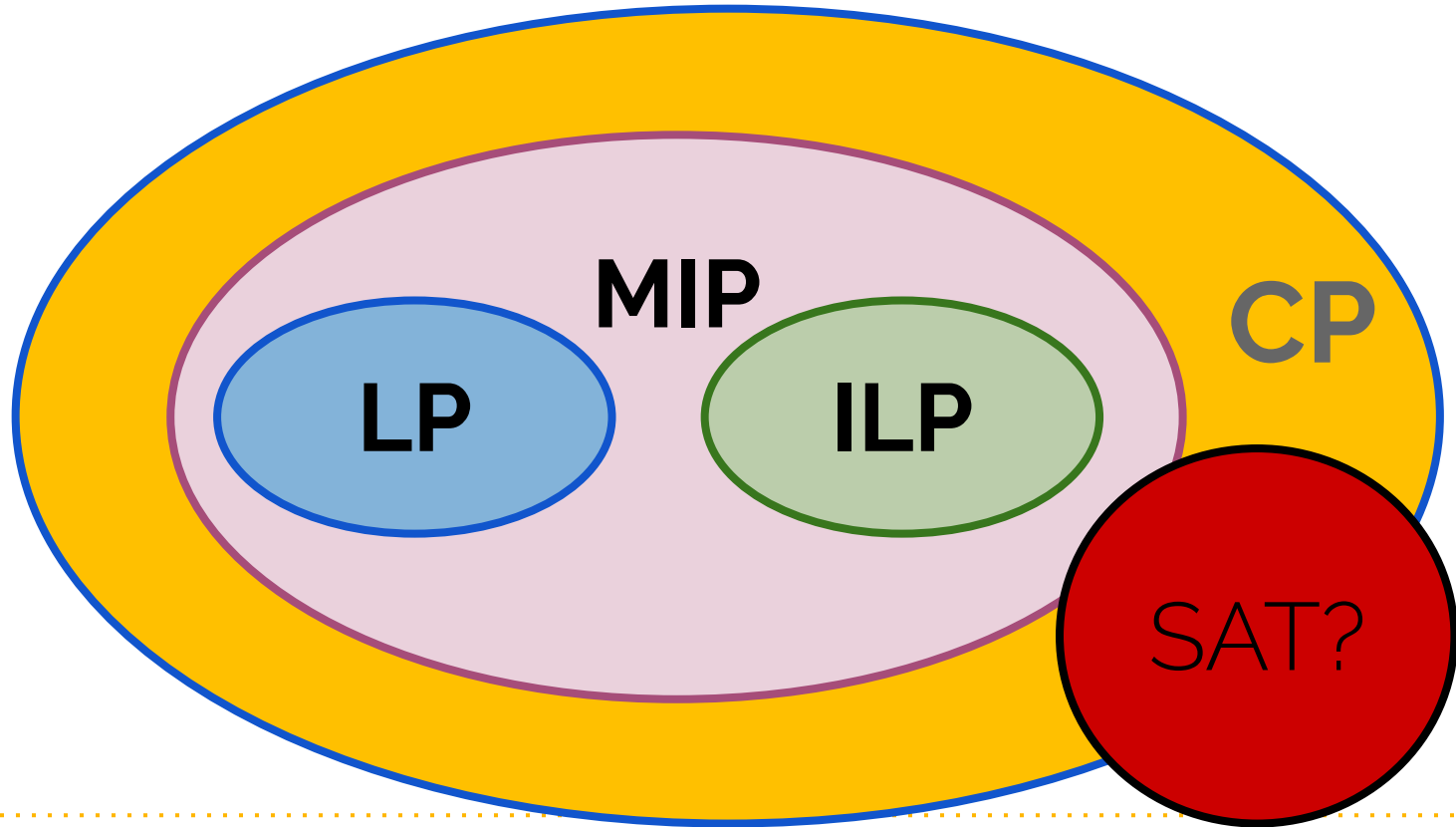


- **Back to SAT!**
- How does CP relate to SAT?

Where does SAT fit into the picture?



Where does SAT fit into the picture?



A loose analogy I've used



Constraint Program



Routing Scheduling



Assignment Packing

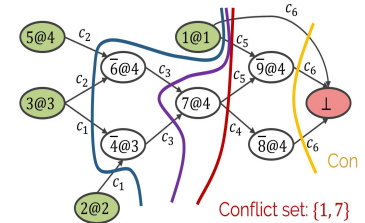
CP-SAT



SAT Formula

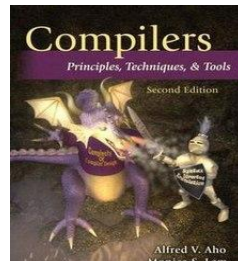
p	q	$p \wedge q$
T	T	T
T	F	F
F	T	F
F	F	F

SAT Solver

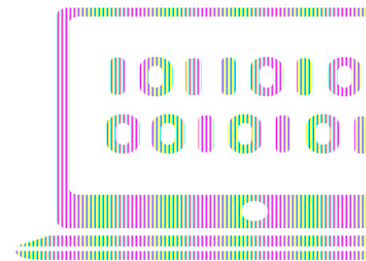


```
1 #include <iostream>
2 using namespace std;
3 int main ()
4 {
5     cout <<"Hello World";
6     return 0;
7 }
8
9
10
```

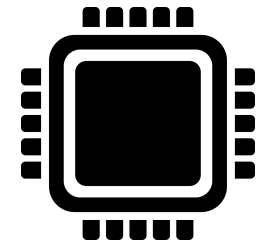
Programming Language



Compiler



Assembly Language



Hardware

Today...



- How does CP-SAT “compile” constraint programs into CNF-SAT formulas?
- Actually, that analogy is **wrong!**
 - CP-SAT does not just turn constraints into clauses and hand it off to a SAT solver...
 - We'll see it's more like a “conversation” btwn CP-SAT & solver
- Disclaimer: this is active research
 - Many details are necessarily left out, and any errors are mine
 - Thanks to: P. Stuckey, O. Ohrimenko, M. Codish, T. Feydy

Recap: CDCL



Conflict Driven Clause Learning

Who remembers?

Recap: CDCL



```
cdcl( $\varphi$ ):  
  if unit_propagate() = CONFLICT: return UNSAT  
  while not all variables have been set:  
    let  $x$  = pick_variable()  
    create new decision level; set  $x$  = T  
    while unit_propagate() = CONFLICT:  
      if level = 0: return UNSAT  
      let (conflict_cls, assrt_lvl) = analyze_conflict()  
      let  $\varphi$  =  $\varphi \cup \{ \text{conflict\_cls} \}$   
      # discard all assignments after asserting level  
      backjump(assrt_lvl)  
  return SAT
```

Recap: CDCL



- Recall: CDCL = **Conflict Driven Clause Learning**
- **Incrementality:** CDCL solvers allow new clauses to be added during the search
- **Conflict analysis**
 - Build implication graph
 - Find set of literals that caused the conflict
 - Learn a new conflict clause

Recap: CDCL

c_1 : $\bar{2} \vee \bar{3} \vee \bar{4}$

c_2 : $\bar{3} \vee \bar{5} \vee \bar{6}$

c_3 : $4 \vee 6 \vee 7$

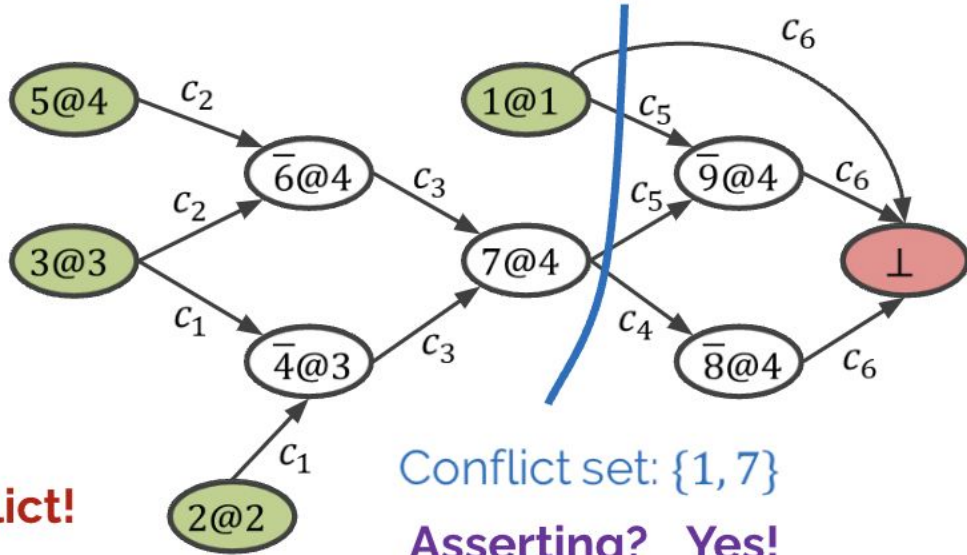
c_4 : $\bar{7} \vee \bar{8}$

c_5 : $\bar{1} \vee \bar{7} \vee \bar{9}$

c_6 : $\bar{1} \vee \bar{8} \vee \bar{9}$

c : $\bar{1} \vee \bar{7}$

Conflict!



Conflict set: $\{1, 7\}$

Asserting? **Yes!**

Level? **1**

Background: CP Solvers



- We'll consider CP over discrete finite domains only (i.e., bounded integer vars)
- Need to understand a bit about how traditional finite domain solvers work first



Background: CP Solvers



- Maintain a domain D that tracks the possible values for each variable
 - Doesn't need to be contiguous (e.g., $\{1, 3, 5\}$)
- Let $\min_D(x)$ and $\max_D(x)$ denote the min and max possible values for variable x in domain D
 - Initially $D(x) = [\text{lb}(x).. \text{ub}(x)]$ for each variable x

Bounds Consistency



- We say a constraint c involving variables x_1, \dots, x_n is **bounds consistent** with domain D if for each x_i :
 - it's possible to set $x_i = \min_D(x_i)$ and still satisfy c , and
 - it's possible to set $x_i = \max_D(x_i)$ and still satisfy c
- **Ex:** $D(x) = [4..7]$, $D(y) = [1..5]$, $D(z) = [-1..2]$ subject to $x = y + z$
 - $x = 4 \rightarrow y = 4, z = 0$ ✓
 - $x = 7 \rightarrow y = 5, z = 2$ ✓
 - $y = 1 \rightarrow x = 4, z = ?$ ✗ not bounds consistent!

In other words, "there exists a solution within the bounds when we set $x_i = \min$ and $x_i = \max$ "

Bounds Consistency



$$D(x) = [4..7], D(y) = [2..5], D(z) = [-1..2]$$

subject to $x = y + z$

$$x = 4 \rightarrow y = 4, z = 0 \quad \checkmark$$

$$y = 5 \rightarrow x = 6, z = 1 \quad \checkmark$$

$$x = 7 \rightarrow y = 5, z = 2 \quad \checkmark$$

$$z = -1 \rightarrow x = 4, y = 5 \quad \checkmark$$

$$y = 2 \rightarrow x = 4, z = 2 \quad \checkmark$$

$$z = 2 \rightarrow x = 6, y = 4 \quad \checkmark$$

Propagators



- A **propagator** for constraint c is an algorithm that accepts a domain D , and returns:
 - A new domain D' where c is bounds consistent with D'
 - Implications “explaining” the updated bounds in D'
- Different constraints have different propagation rules for finding D'

Propagator for $x = y + z$



- How to ensure bounds consistency for $x = y + z$?
- We can rewrite to isolate each variable:

$$x = y + z \quad y = x - z \quad z = x - y$$

- Now we can derive a pair of inequalities for each:
 - $x \geq \min_D(y) + \min_D(z)$ and $x \leq \max_D(y) + \max_D(z)$
 - $y \geq \min_D(x) - \max_D(z)$ and $y \leq \max_D(x) - \min_D(z)$
 - $z \geq \min_n(x) - \max_n(y)$ and $z \leq \max_n(x) - \min_n(y)$

Propagator for $x = y + z$



- What are “explanations”?
- **Ex:** $D(x) = [4..7]$, $D(y) = [1..5]$, $D(z) = [-1..2]$
- Since $y \geq \min_D(x) - \max_D(z) = 4 - 2 = 2$, we update the domain of y to $D'(y) = [2..5]$
- The explanation for this update is the implication:

$$(x \geq 4) \wedge (z \leq 2) \Rightarrow y \geq 2$$

Bounds Consistency



$$D(x) = [4..7], D(y) = [2..5], D(z) = [-1..2]$$

subject to $x = y + z$

$$x = 4 \rightarrow y = 4, z = 0 \quad \checkmark$$

$$y = 5 \rightarrow x = 6, z = 1 \quad \checkmark$$

$$x = 7 \rightarrow y = 5, z = 2 \quad \checkmark$$

$$z = -1 \rightarrow x = 4, y = 5 \quad \checkmark$$

$$y = 2 \rightarrow x = 4, z = 2 \quad \checkmark$$

$$z = 2 \rightarrow x = 6, y = 4 \quad \checkmark$$

Finite Domain Propagation



Many traditional CP solvers use **finite domain propagation**:

- Start with the initial domain D_0 specified by the user
- Try adding a new constraint c (e.g. assigning a variable)
- Repeatedly run all constraint propagators on D until:
 - A var has no possible values: BACKTRACK, add $\neg c$!
 - Nothing changes: add another constraint and repeat
- Does this sound familiar?

Ex: Finite Domain Propagation



$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$
s.t. $x_2 \leq x_5$, $\text{AllDifferent}([x_1, x_2, x_3, x_4])$, $x_1 + x_2 + x_3 + x_4 \leq 9$

Ex: Finite Domain Propagation



$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$
s.t. $x_2 \leq x_5$, $\text{AllDifferent}([x_1, x_2, x_3, x_4])$, $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$
$D(x_1)$	{1}
$D(x_2)$	[1..4]
$D(x_3)$	[1..4]
$D(x_4)$	[1..4]
$D(x_5)$	[1..4]

Domain D_1

Ex: Finite Domain Propagation



$$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$$

s.t. $x_2 \leq x_5$, AllDifferent($[x_1, x_2, x_3, x_4]$), $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$	AllDiff
$D(x_1)$	{1}	{1}
$D(x_2)$	[1..4]	[2..4]
$D(x_3)$	[1..4]	[2..4]
$D(x_4)$	[1..4]	[2..4]
$D(x_5)$	[1..4]	[1..4]

Domain D_1

Ex: Finite Domain Propagation



$$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$$

s.t. $x_2 \leq x_5$, AllDifferent($[x_1, x_2, x_3, x_4]$), $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$	AllDiff	$x_2 \leq x_5$
$D(x_1)$	{1}	{1}	{1}
$D(x_2)$	[1..4]	[2..4]	[2..4]
$D(x_3)$	[1..4]	[2..4]	[2..4]
$D(x_4)$	[1..4]	[2..4]	[2..4]
$D(x_5)$	[1..4]	[1..4]	[2..4]

Domain D_1

Ex: Finite Domain Propagation



$$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$$

s.t. $x_2 \leq x_5$, AllDifferent($[x_1, x_2, x_3, x_4]$), $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$	AllDiff	$x_2 \leq x_5$	$x_5 \leq 2$
$D(x_1)$	{1}	{1}	{1}	{1}
$D(x_2)$	[1..4]	[2..4]	[2..4]	[2..4]
$D(x_3)$	[1..4]	[2..4]	[2..4]	[2..4]
$D(x_4)$	[1..4]	[2..4]	[2..4]	[2..4]
$D(x_5)$	[1..4]	[1..4]	[2..4]	{2}

Domain D_1

Domain D_2

Ex: Finite Domain Propagation



$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$
s.t. $x_2 \leq x_5$, AllDifferent($[x_1, x_2, x_3, x_4]$), $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$	AllDiff	$x_2 \leq x_5$	$x_5 \leq 2$	$x_2 \leq x_5$
$D(x_1)$	{1}	{1}	{1}	{1}	{1}
$D(x_2)$	[1..4]	[2..4]	[2..4]	[2..4]	{2}
$D(x_3)$	[1..4]	[2..4]	[2..4]	[2..4]	[2..4]
$D(x_4)$	[1..4]	[2..4]	[2..4]	[2..4]	[2..4]
$D(x_5)$	[1..4]	[1..4]	[2..4]	{2}	{2}

Domain D_1

Domain D_2

Ex: Finite Domain Propagation



$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$
 s.t. $x_2 \leq x_5$, AllDifferent($[x_1, x_2, x_3, x_4]$), $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$	AllDiff	$x_2 \leq x_5$	$x_5 \leq 2$	$x_2 \leq x_5$	AllDiff
$D(x_1)$	{1}	{1}	{1}	{1}	{1}	{1}
$D(x_2)$	[1..4]	{2..4}	[2..4]	[2..4]	{2}	{2}
$D(x_3)$	[1..4]	{2..4}	[2..4]	[2..4]	[2..4]	{3..4}
$D(x_4)$	[1..4]	{2..4}	[2..4]	[2..4]	[2..4]	{3..4}
$D(x_5)$	[1..4]	[1..4]	{2..4}	{2}	{2}	{2}

Domain D_1

Domain D_2

Ex: Finite Domain Propagation



$$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$$

s.t. $x_2 \leq x_5$, AllDifferent($[x_1, x_2, x_3, x_4]$), $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$	AllDiff	$x_2 \leq x_5$	$x_5 \leq 2$	$x_2 \leq x_5$	AllDiff	$\Sigma \leq 9$
$D(x_1)$	{1}	{1}	{1}	{1}	{1}	{1}	{1}
$D(x_2)$	[1..4]	[2..4]	[2..4]	[2..4]	{2}	{2}	{2}
$D(x_3)$	[1..4]	[2..4]	[2..4]	[2..4]	[2..4]	[3..4]	{3}
$D(x_4)$	[1..4]	[2..4]	[2..4]	[2..4]	[2..4]	[3..4]	{3}
$D(x_5)$	[1..4]	[1..4]	[2..4]	{2}	{2}	{2}	{2}

Domain D_1

Domain D_2

Ex: Finite Domain Propagation



$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$
 s.t. $x_2 \leq x_5$, AllDifferent($[x_1, x_2, x_3, x_4]$), $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$	AllDiff	$x_2 \leq x_5$	$x_5 \leq 2$	$x_2 \leq x_5$	AllDiff	$\Sigma \leq 9$	AllDiff
$D(x_1)$	{1}	{1}	{1}	{1}	{1}	{1}	{1}	{1}
$D(x_2)$	[1..4]	[2..4]	[2..4]	[2..4]	{2}	{2}	{2}	{2}
$D(x_3)$	[1..4]	[2..4]	[2..4]	[2..4]	[2..4]	[3..4]	{3}	\emptyset
$D(x_4)$	[1..4]	[2..4]	[2..4]	[2..4]	[2..4]	[3..4]	{3}	\emptyset
$D(x_5)$	[1..4]	[1..4]	[2..4]	{2}	{2}	{2}	{2}	{2}

Domain D_1

Domain D_2

Ex: Finite Domain Propagation



$$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$$

s.t. $x_2 \leq x_5$, AllDifferent($[x_1, x_2, x_3, x_4]$), $x_1 + x_2 + x_3 + x_4 \leq 9$

	$x_1 = 1$	AllDiff	$x_2 \leq x_5$	$x_5 > 2$	etc...
$D(x_1)$	{1}	{1}	{1}	{1}	
$D(x_2)$	[1..4]	[2..4]	[2..4]	[2..4]	
$D(x_3)$	[1..4]	[2..4]	[2..4]	[2..4]	
$D(x_4)$	[1..4]	[2..4]	[2..4]	[2..4]	
$D(x_5)$	[1..4]	[1..4]	[2..4]	[3..4]	

Backtrack!

Domain D_1

Domain D_2

FD Propagation is Like DPLL



- Adding a constraint is like making a decision
- Running constraint propagators is like unit propagation
- Backtracking is like... backtracking
- So why don't we try to just do this all in SAT?

Representing CP as SAT?



- First question: what are the boolean variables?
- **Attempt 1:** for each CP var x , create boolean variables $\llbracket x = i \rrbracket$ for $\text{lb}(x) \leq i \leq \text{ub}(x)$
 - Number of variables is linear in size of domain
 - Issue: need very long clauses to represent inequalities (e.g. $x \leq 10$)
 - Poor propagation strength
- **Attempt 2:** logarithmic encoding (create a boolean variable for each bit of x)
 - Logarithmic in size of domain, but even worse propagation strength



Order Encoding

- For each CP var x , create boolean variables:
 - $\llbracket x = i \rrbracket$ for $\text{lb}(x) \leq i \leq \text{ub}(x)$
 - $\llbracket x \leq i \rrbracket$ for $\text{lb}(x) \leq i \leq \text{ub}(x)$
- Note that $(x \geq i) \equiv \neg \llbracket x \leq i - 1 \rrbracket$ and $(x \neq i) \equiv \neg \llbracket x = i \rrbracket$
- Need to add consistency clauses:
 - $\llbracket x \leq i \rrbracket \Rightarrow \llbracket x \leq i + 1 \rrbracket$ for $\text{lb}(x) \leq i \leq \text{ub}(x) - 1$
 - $\llbracket x = i \rrbracket \Leftrightarrow \llbracket x \leq i \rrbracket \wedge \neg \llbracket x \leq i - 1 \rrbracket$
- Linear in size of domain; good propagation strength

Adding a CP constraint in SAT



- How can we write the constraint $x = y + z$ with clauses?
- Need to enforce it for each possible value of x, y, z
- For each $lb \leq i, j \leq ub$, add clauses:
 - $\llbracket y = i \rrbracket \wedge \llbracket z = j \rrbracket \Rightarrow \llbracket x = i + j \rrbracket$
 - $\llbracket x = i \rrbracket \wedge \llbracket z = j \rrbracket \Rightarrow \llbracket y = i - j \rrbracket$
 - $\llbracket x = i \rrbracket \wedge \llbracket y = j \rrbracket \Rightarrow \llbracket z = i - j \rrbracket$
- How many clauses? $O(|ub - lb|^2)$
 - What if we sum more variables? Exponential blowup!

Lazy Clause Generation



- **Key observation:** although it takes a lot of clauses to represent a CP constraint, most clauses are never used
- **Lazy clause generation:** rather than generate all these clauses before solving, just generate the ones we need, when we need them!
- OK, but how does that actually work...

Lazy Clause Generation



- Recall that FD propagators return an “explanation” for updating bounds, e.g. $(x \geq 4) \wedge (z \leq 2) \Rightarrow y \geq 2$
- Easy to express these explanations as clauses
- Can run propagators during execution of CDCL solver, then add explanation clauses to formula
 - If we only introduce explanation clauses when the LHS of the implication is currently true, they will immediately become unit clauses!

LCG Pseudocode



```
lazy_clause_generation(constraint_program):  
    let P = make_propagators(constraint_program)  
    if lcg_propagate() = CONFLICT: return INFEASIBLE  
    while not all variables have been set:  
        let x = pick_variable()  
        create new decision level; set x = T  
        while lcg_propagate(P,  $\varphi$ ) = CONFLICT:  
            if level = 0: return INFEASIBLE  
            let (cls, lvl) = analyze_conflict()  
            let  $\varphi$  =  $\varphi \cup \{ \text{cls} \}$   
            backjump(lvl)  
    return FEASIBLE
```

```
lcg_propagate(P,  $\varphi$ ):  
    while True:  
        if unit_prop() = CONFLICT:  
            return CONFLICT  
        for propagator p  $\in$  P:  
            let expl_clauses = p( $\varphi$ )  
            let  $\varphi$  =  $\varphi \cup \text{expl\_clauses}$   
        if  $\varphi$  did not change:  
            return SUCCESS
```

LCG Example



$$D_0(x_1) = D_0(x_2) = D_0(x_3) = D_0(x_4) = D_0(x_5) = [1..4]$$

$$\text{s.t. } x_2 \leq x_5, \text{ AllDifferent}([x_1, x_2, x_3, x_4]), x_1 + x_2 + x_3 + x_4 \leq 9$$

$$x_1 = 1$$

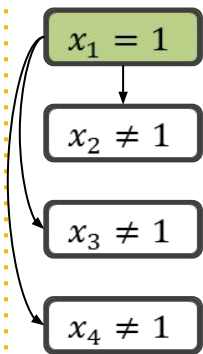
Decision: $\llbracket x_1 = 1 \rrbracket$

(Note: For simplicity, some clauses are ignored in this example, and decision levels are left out; don't take it too seriously.)

LCG Example



AllDiff



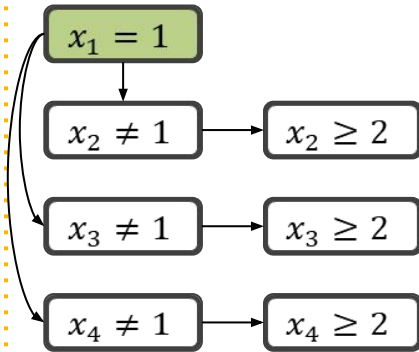
Propagate AllDifferent($[x_1, x_2, x_3, x_4]$)

Explanations: $x_1 = 1 \Rightarrow x_2 \neq 1$; $x_1 = 1 \Rightarrow x_3 \neq 1$; $x_1 = 1 \Rightarrow x_4 \neq 1$

LCG Example



AllDiff

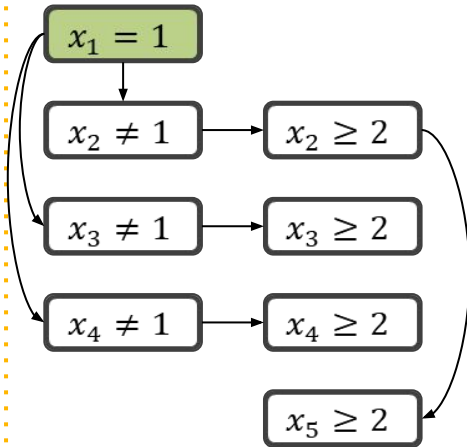


Propagate consistency clauses

LCG Example



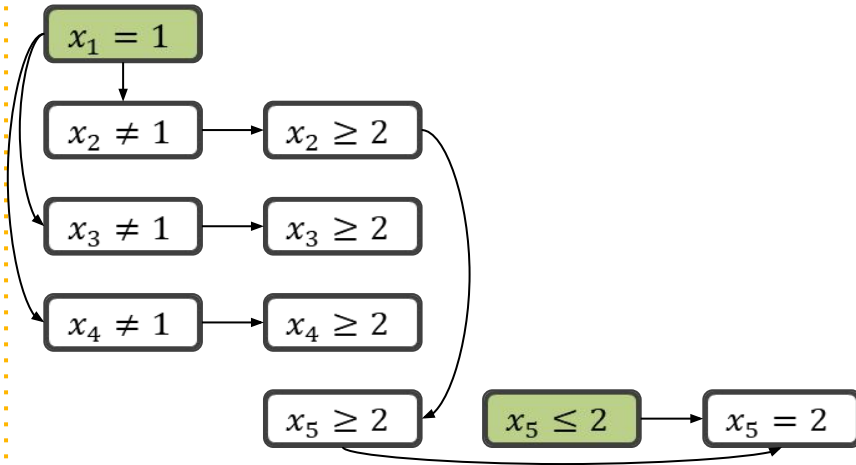
AllDiff $x_2 \leq x_5$



LCG Example



AllDiff $x_2 \leq x_5$



Decision: $\llbracket x_5 \leq 2 \rrbracket$

Propagate consistency constraints

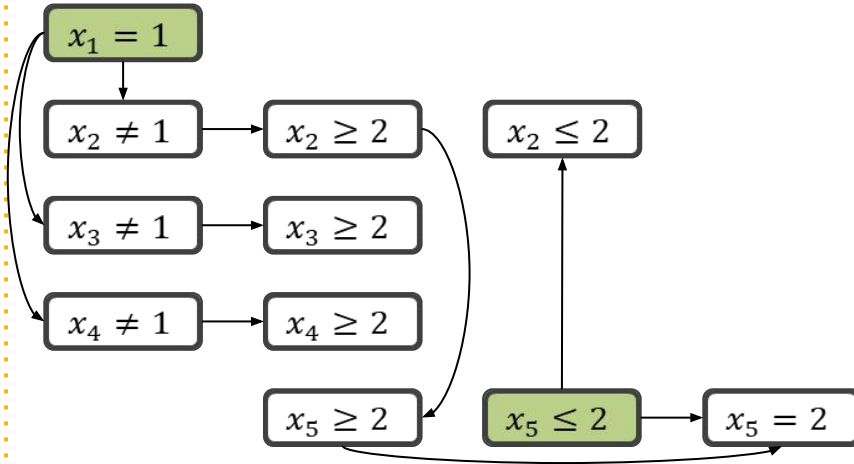
LCG Example



AllDiff

$$x_2 \leq x_5$$

$$x_2 \leq x_5$$



Propagate $x_2 \leq x_5$

Explanations: $x_5 \leq 2 \Rightarrow x_2 \leq 2$

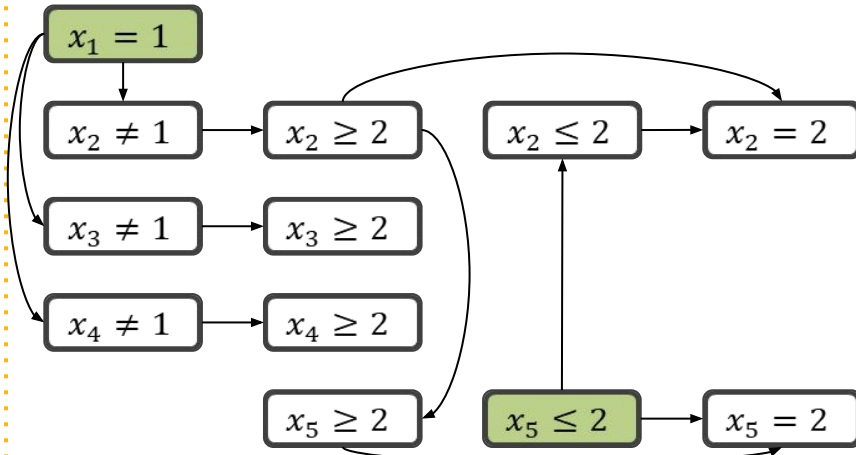
LCG Example



AllDiff

$$x_2 \leq x_5$$

$$x_2 \leq x_5$$



Propagate consistency constraints



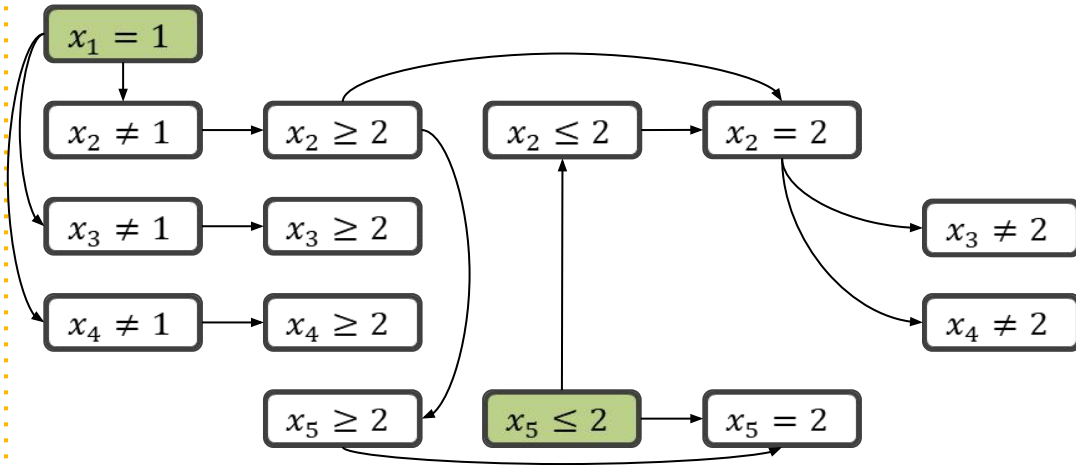
LCG Example

AllDiff

$x_2 \leq x_5$

$x_2 \leq x_5$

AllDiff



Propagate AllDifferent($[x_1, x_2, x_3, x_4]$)

Explanations: $x_2 = 2 \Rightarrow x_3 \neq 2$; $x_2 = 2 \Rightarrow x_4 \neq 2$

LCG Example

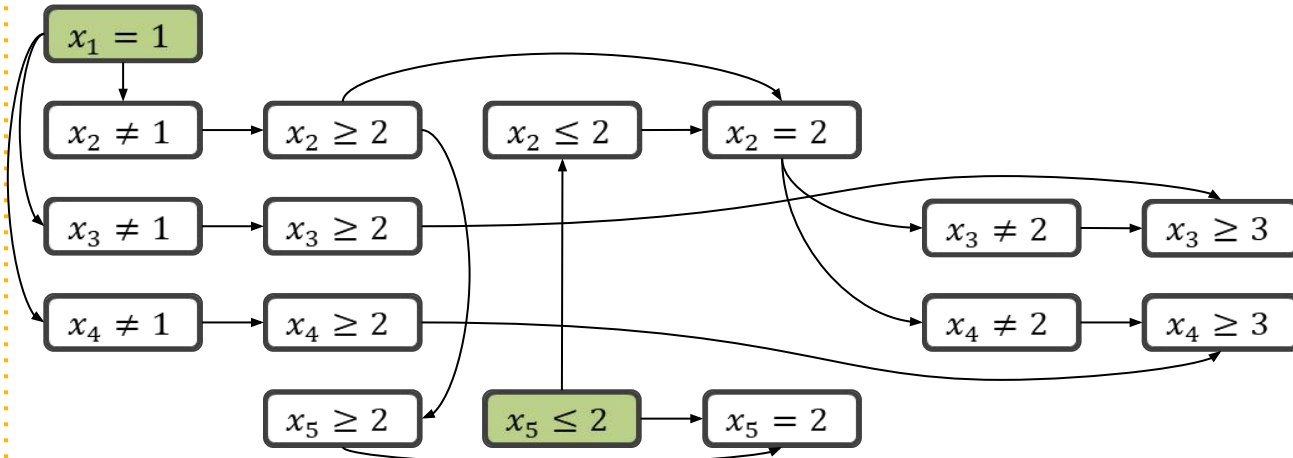


AllDiff

$x_2 \leq x_5$

$x_2 \leq x_5$

AllDiff



Propagate consistency constraints

LCG Example



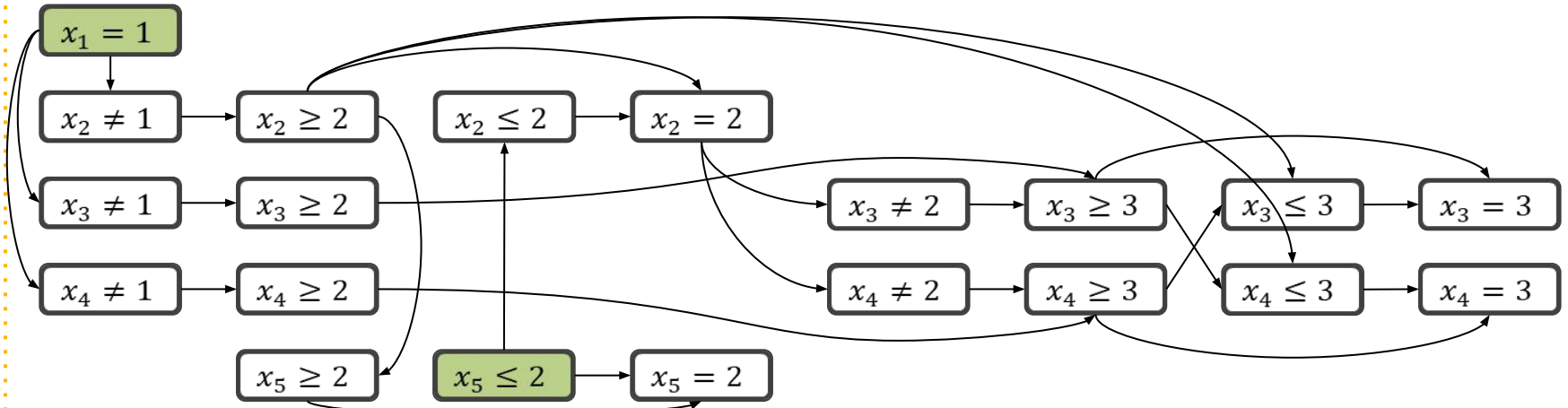
AllDiff

$x_2 \leq x_5$

$x_2 \leq x_5$

AllDiff

$\sum \leq 9$



Propagate consistency constraints

LCG Example



AllDiff

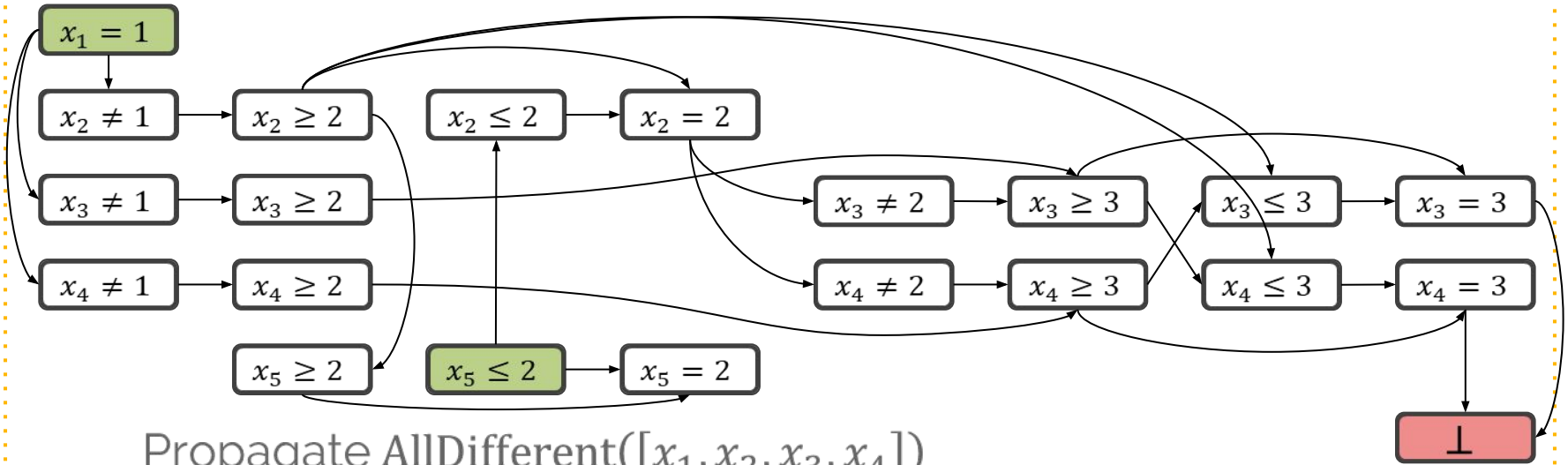
$x_2 \leq x_5$

$x_2 \leq x_5$

AllDiff

$\Sigma \leq 9$

AllDiff



Explanations: $x_3 = 3 \wedge x_4 = 3 \Rightarrow F$

LCG Example



AllDiff

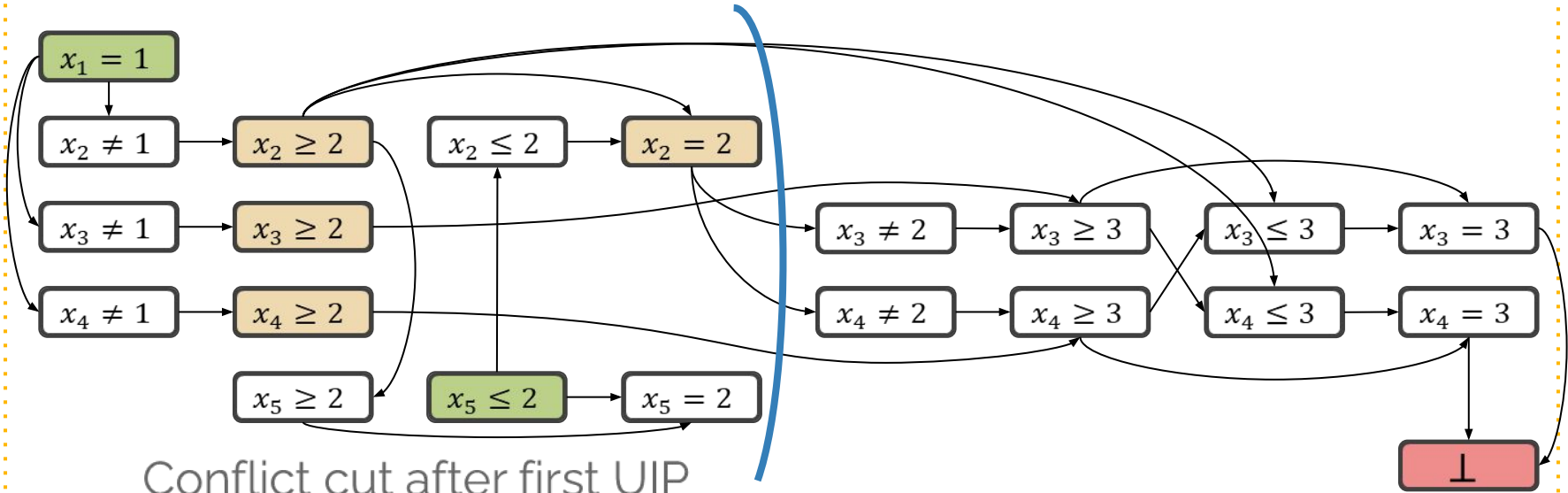
$x_2 \leq x_5$

$x_2 \leq x_5$

AllDiff

$\sum \leq 9$

AllDiff



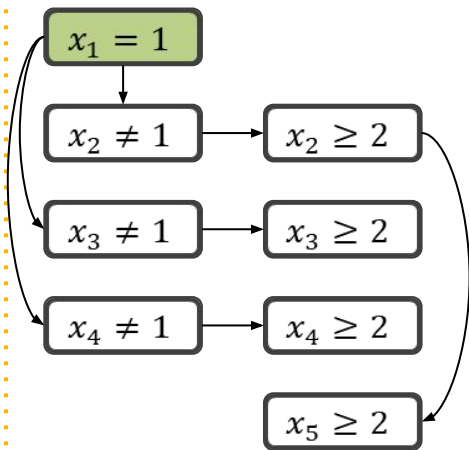
Conflict cut after first UIP

Learned clause: $\neg[x_2 \geq 2] \vee \neg[x_3 \geq 2] \vee \neg[x_4 \geq 2] \vee \neg[x_2 = 2]$

LCG Example



AllDiff $x_2 \leq x_5$



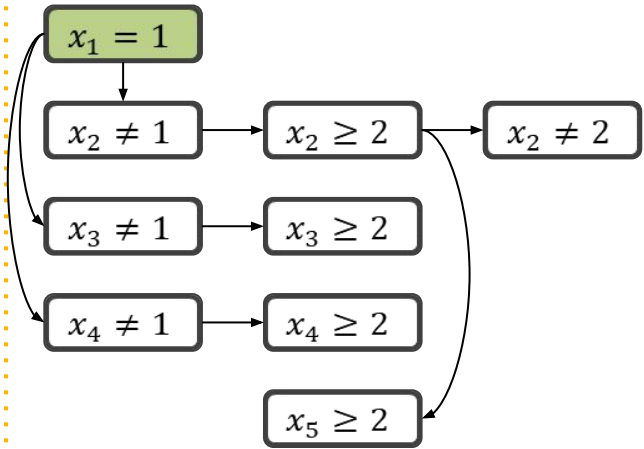
Backtrack to asserting level!

Learned clause: $\neg[x_2 \geq 2] \vee \neg[x_3 \geq 2] \vee \neg[x_4 \geq 2] \vee \neg[x_2 = 2]$

LCG Example



AllDiff $x_2 \leq x_5$



Propagate from learned clause

Learned clause: $\neg[x_2 \geq 2] \vee \neg[x_3 \geq 2] \vee \neg[x_4 \geq 2] \vee \neg[x_2 = 2]$

Explanation Deletion



- Explanation clauses are needed for immediate unit propagation and for generating learned clauses
- But when we backtrack past the explanations, may not need them anymore
 - Can delete from formula



Lazy Boolean Variable Creation

- Many of the boolean variables are never actually used
- **Idea:** create boolean variables when we need them
- **Array encoding:** initially only create $\llbracket x \leq i \rrbracket$ variables
 - Create $\llbracket x = i \rrbracket$ variables on demand
 - Don't forget to add clause: $\llbracket x = i \rrbracket \Leftrightarrow \llbracket x \leq i \rrbracket \wedge \neg \llbracket x \leq i - 1 \rrbracket$
- **List encoding:** create both types of variables on demand!
 - When creating $\llbracket x \leq i \rrbracket$, add clauses:
 - $\llbracket x \leq i \rrbracket \Rightarrow \llbracket x \leq i_{\text{next}} \rrbracket$, where i_{next} is next-higher existing bnd

Lazy Variable Tradeoffs



- List encoding has fewer variables, so it can succeed on large domains where array encoding fails
- Array encoding interacts better with clause learning
 - This is significant!
- List encoding is trickier to implement

References



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