



**Off the trail:  
re-examining the CDCL algorithm.**

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University of Toronto**

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# Overview

- Using the standard (historical) description, the trail seems vital to the completeness of DPLL.
- Paradigms and descriptions change
- The trail is not as important as it may seem
  - Is simply an efficient way of deciding which variable to flip
  - No inherent importance to the algorithm
- Current CDCL algorithms can be reformulated as local search with a complicated heuristic

# DPLL Algorithm

Given:  $\phi$  - a formula in CNF

**Solve** ( $\phi$  )

$\phi \leftarrow \text{unitPropagate}(\phi)$

**if**  $\phi$  reduces to a constant, return  $\phi$

$v \leftarrow$  'best' unassigned var

**return**  $\text{Solve}(\phi|_v) \vee \text{Solve}(\phi|_{\neg v})$

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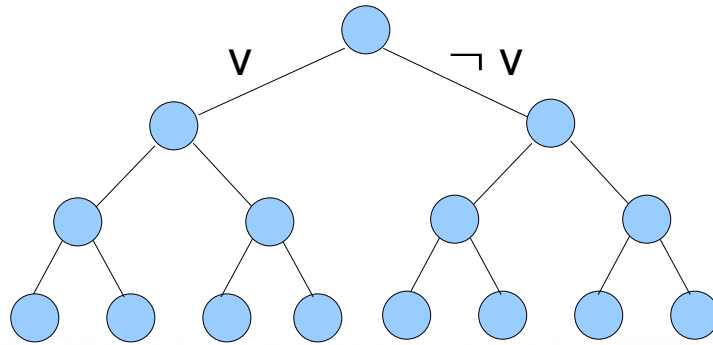
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Given:  $\phi$  - a formula in CNF  
 $\pi \leftarrow \emptyset$

**while** (TRUE)

UnitPropagate(  $\phi$  ,  $\pi$  )

**if** reduce(  $\phi$  ,  $\pi$  ) contains an empty clause

**if** no decisions **then** return FALSE

$v \leftarrow$  last decision

$\pi \leftarrow$  backtrack(lvl[v])

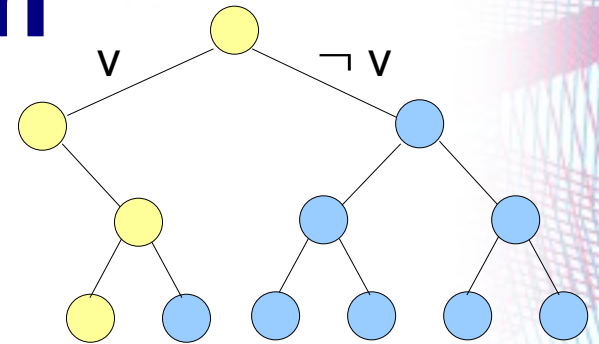
$\pi.append(\neg v)$

**else if**  $\phi$  is TRUE under  $\pi$  **then** return TRUE

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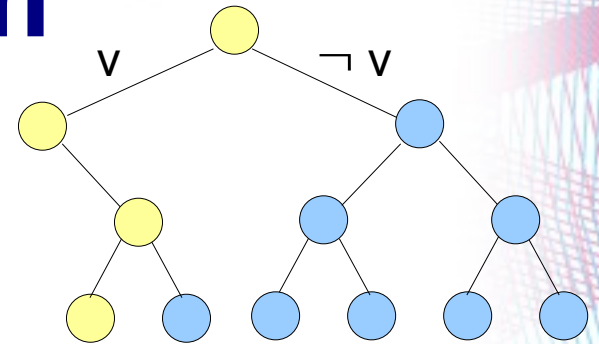
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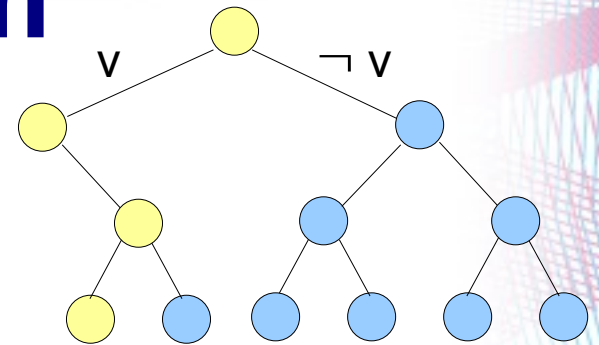
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**while** (TRUE)

UnitPropagate( $\phi \cup C$ ,  $\pi$ )

**if** reduce( $\phi \cup C$ ,  $\pi$ ) contains an empty clause

$c' \leftarrow \text{clauseLearn}(\phi \cup C, \pi)$

**if**  $c' = \emptyset$  **then** return FALSE

$C \leftarrow C \cup \{c'\}$

$\pi \leftarrow \text{backtrack}(c')$

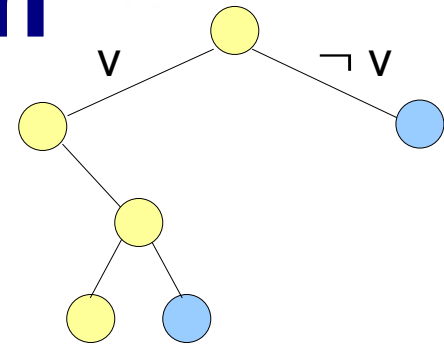
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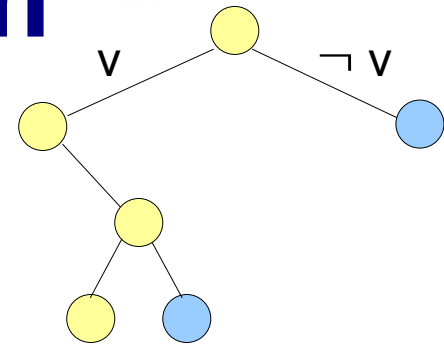
$C \leftarrow C \cup \{c'\}$

$\pi \leftarrow \text{backtrack}(c')$

**else if**  $\phi$  is TRUE under  $\pi$  **then** return TRUE

**else** **Clause learning:**

- Learn from conflicts
- *Empowering* clauses
- Without deletion,  
guarantees completeness



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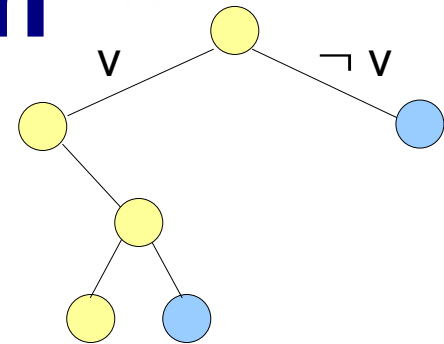
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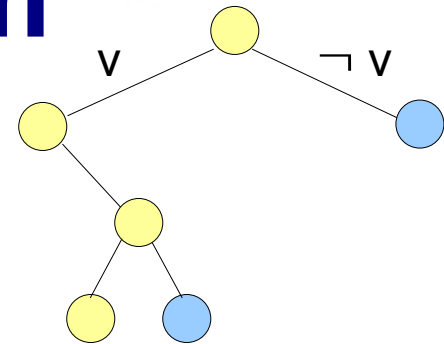
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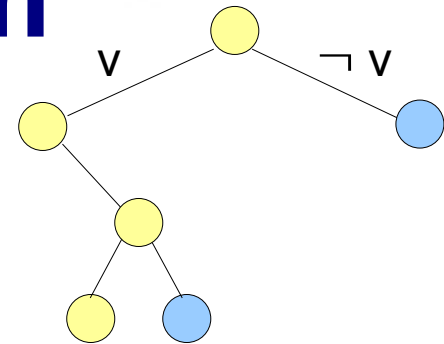
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$v \leftarrow$  **unassigned var with largest VSIDS**

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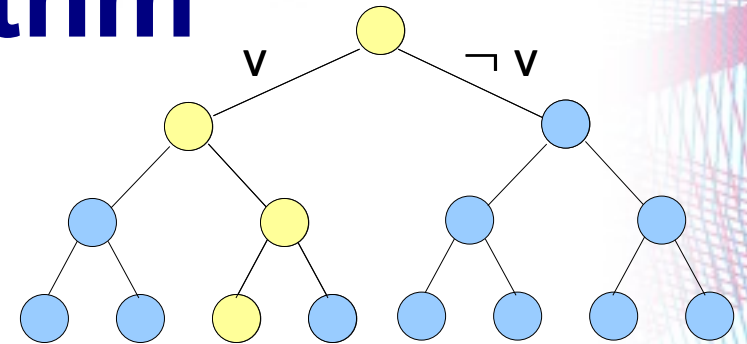
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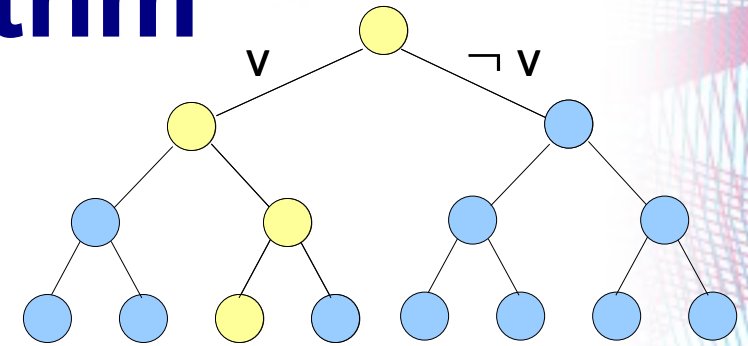
$\pi$ .append( $v$ )

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# DPLL Algorithm

**Restart to a different part  
of search space**



```
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if reduce( $\phi \cup C, \pi$ ) contains an empty clause  
   $c' \leftarrow$  clauseLearn( $\phi \cup C, \pi$ )  
  if  $c' = \emptyset$  then return FALSE  
   $C \leftarrow C \cup \{c'\}$   
   $\pi \leftarrow$  backtrack( $c'$ )
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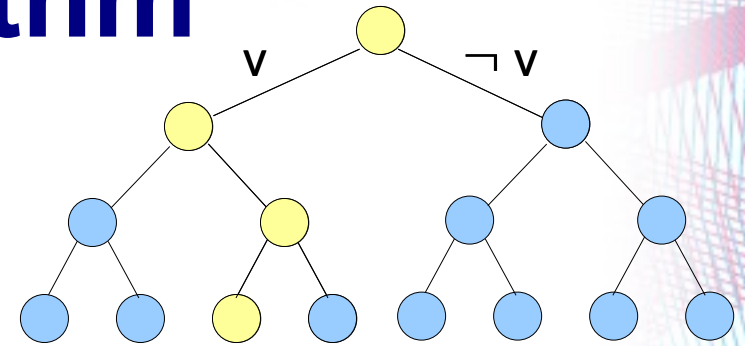
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   $v \leftarrow$  phase[v]
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```
   $\pi$ .append(v)
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if timeToRestart() then backtrack(0)
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# DPLL Algorithm

**Restart to a different part  
of search space  
+ Progress saving**



```
if reduce( $\phi \cup C, \pi$ ) contains an empty clause  
   $c' \leftarrow \text{clauseLearn}(\phi \cup C, \pi)$   
  if  $c' = \emptyset$  then return FALSE  
   $C \leftarrow C \cup \{c'\}$   
   $\pi \leftarrow \text{backtrack}(c')$ 
```

```
else if  $\phi$  is TRUE under  $\pi$  then return TRUE  
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```

```
   $v \leftarrow$  unassigned var with largest VSIDS
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   $v \leftarrow \text{phase}[v]$ 
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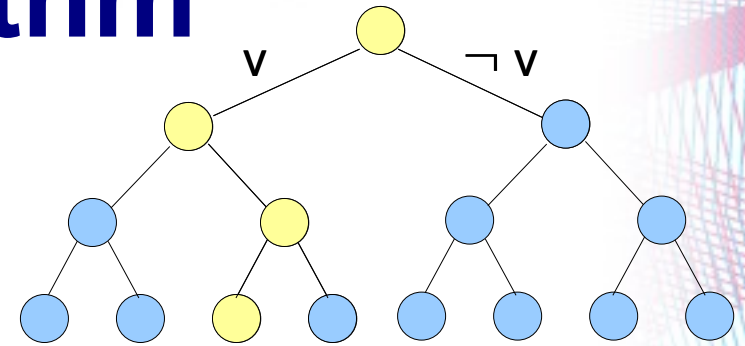
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# DPLL Algorithm

**Restart to a different part  
of search space  
+ Progress saving  
+ VSIDS**



```
contains an empty clause
c' ← clauseLearn( $\phi \cup C, \pi$ )
if c' =  $\emptyset$  then return FALSE
C ← C  $\cup$  {c'}
 $\pi$  ← backtrack(c')
```

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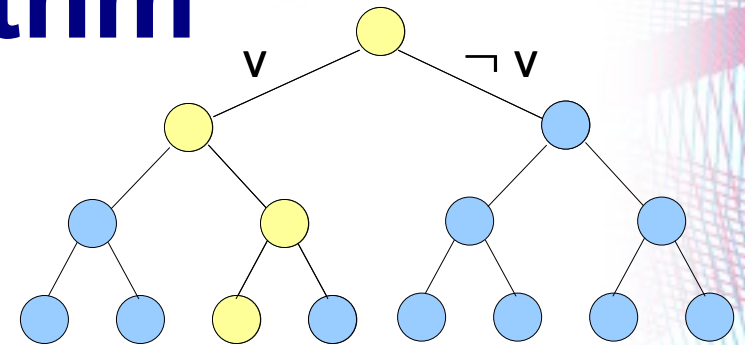
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v ← unassigned var with largest VSIDS
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v ← phase[v]
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 $\pi$ .append(v)
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# DPLL Algorithm



~~Restart to a different part  
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+ Progress saving  
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while  $\phi$  contains an empty clause  
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   $c' \leftarrow \text{clauseLearn}(\phi \cup C, \pi)$   
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   $v \leftarrow \text{phase}[v]$ 
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```
   $\pi.\text{append}(v)$ 
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```
if timeToRestart() then backtrack(0)
```

# Re-creating the trail

**a** (5.4)

**b** (2.2)

**c** (2.5)

**d** (4.1)

**e** (3.2)

**f** (2.3)

**g** (3.1)

**h** (4.9)

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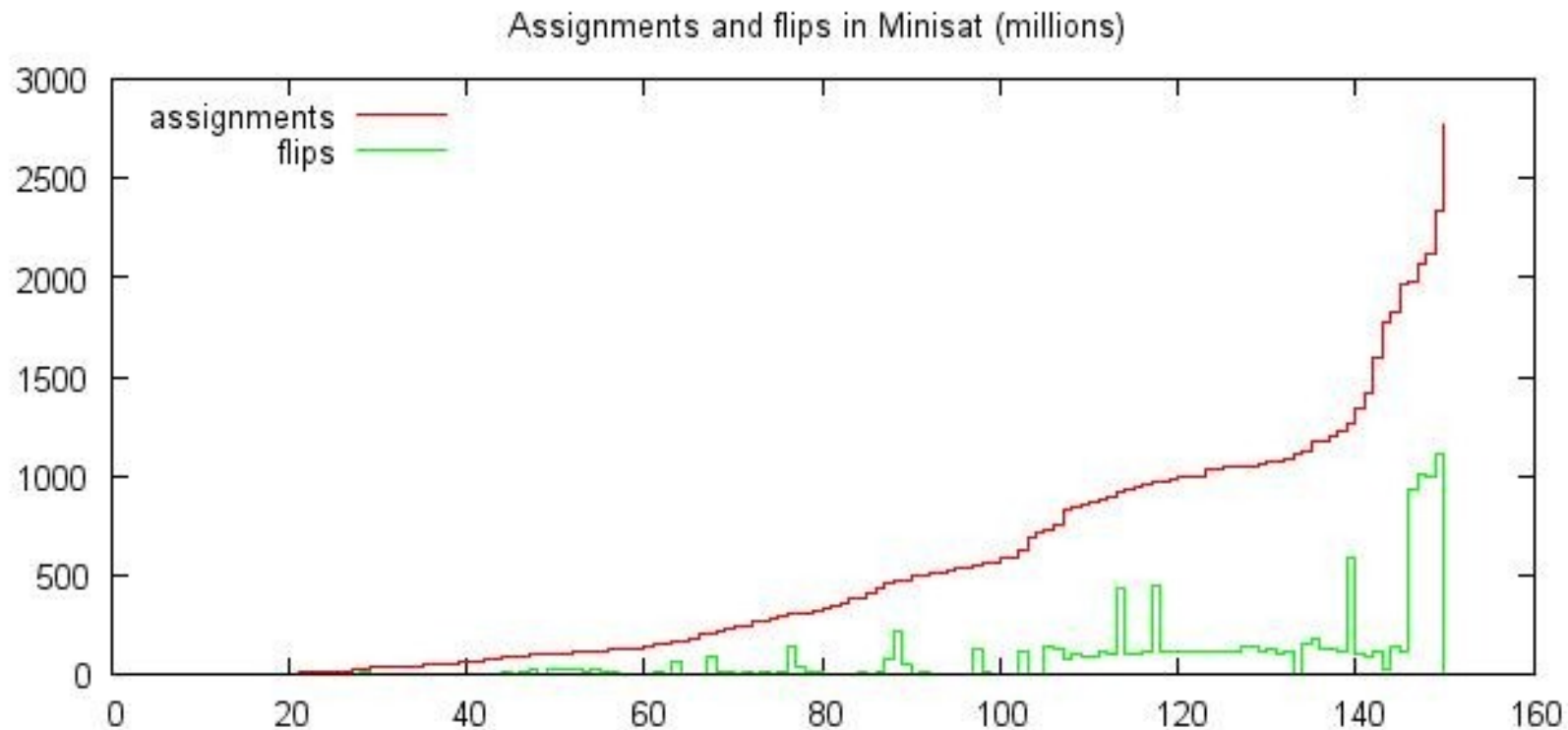
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Effect of restart: the trail is updated to  
order decisions by heuristic

# Assignments vs. flips



- **Assignment:** any time a variable gets a value
- **Flip:** any time a variable gets a value that is *different from its phase setting*

# Concentrate on Flips

- Imagine a complete assignment:
  - Variable's value, if it exists
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  - Every flip has a *reason*:

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  - Guaranteed a flip after every clause learning episode; or caused by other assignments
- Decision variables are never flipped
  - Every flip has a *reason*:
    - A clause which contains the flipped variable
    - The flipped variable is the “least important” in that clause.

# Intuition

- Variables with high heuristic values are “important”
- A false clause means a flip. We want to flip the least important variable.
- However: if  $(\alpha \rightarrow x)$  and we flip  $x$ , then:
  - Either we'll need to flip  $x$  back
  - Or we'll need to flip a variable from  $\alpha$
- So: any variable implied by important variables is important

# Local Search

Given:  $\phi$  - a formula in CNF

```
while ( $\phi|_I$  is not TRUE)
```

```
    I  $\leftarrow$  initValues()
```

```
    while  $\phi|_I$  contains FALSE clauses
```

```
        if timeToRestart() then continue outer
```

```
        v  $\leftarrow$  pickVar(I)
```

```
        flip(v)
```

```
return TRUE
```

# Local Search

- Want to get “closer to a solution”
  - estimating is very difficult
  - estimates are unreliable
  - lots of local minima
- Escaping local minima:
  - generate a new clause that would change the landscape
  - if a clause is guaranteed to be new, get completeness

# Local Search

- For better clauses, want an implication graph.
- How to generate it from existing assignment  $I$ ?
  - CDLS: “simulate UP until it first deviates from  $I$ ”

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( e ¬d ¬f ¬h )

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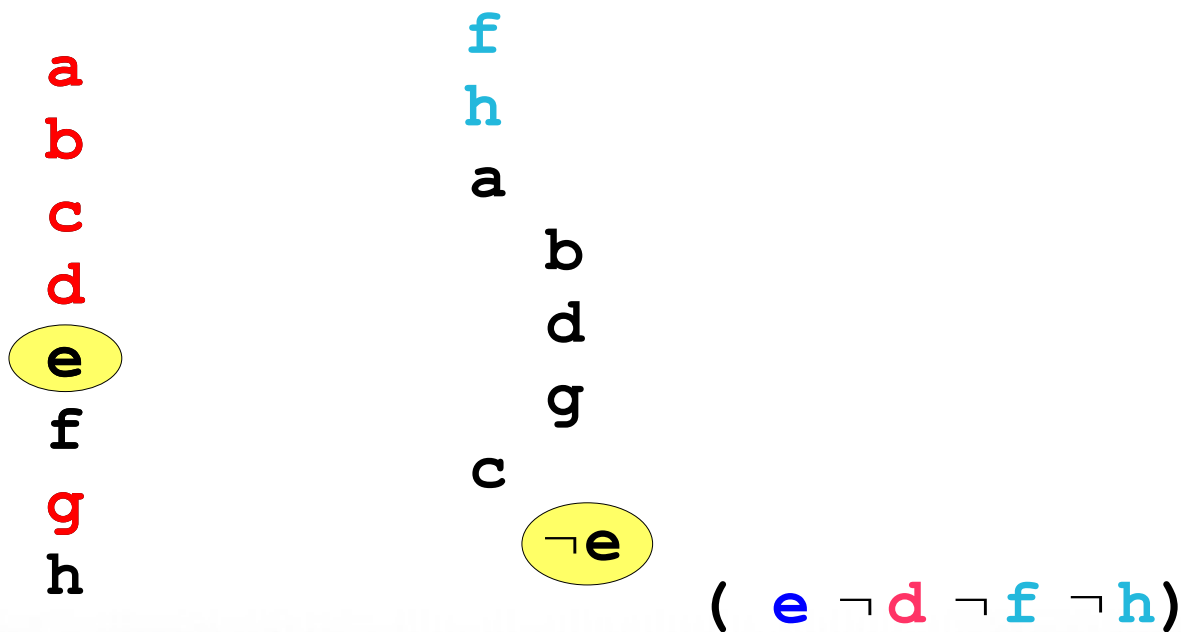
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( e ¬ d ¬ f ¬ h )

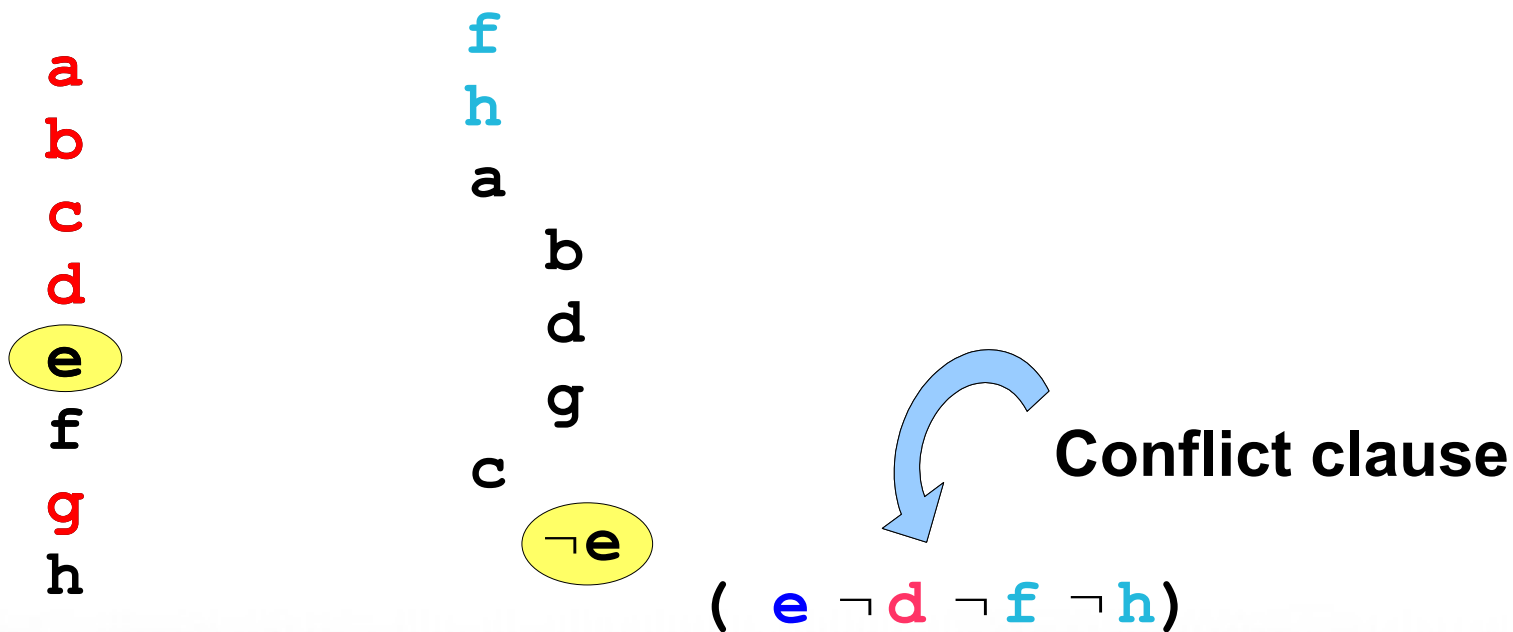
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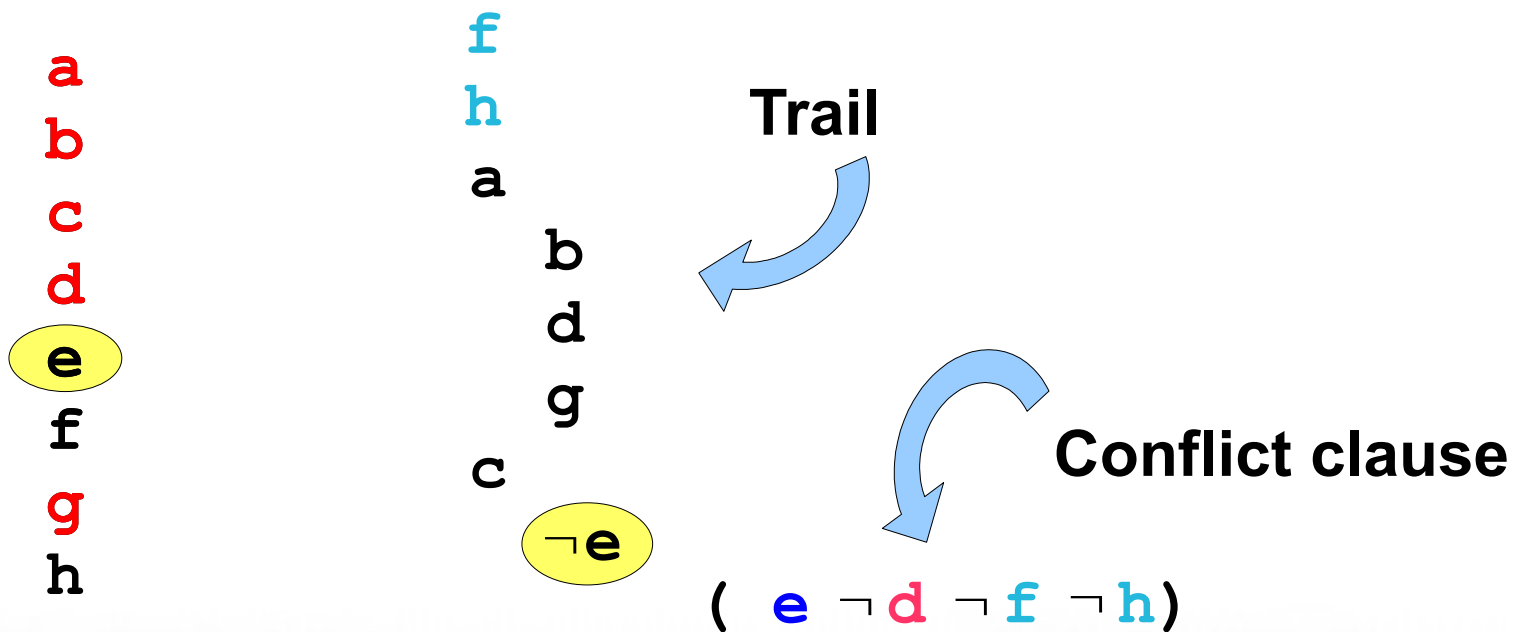
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# Local Search

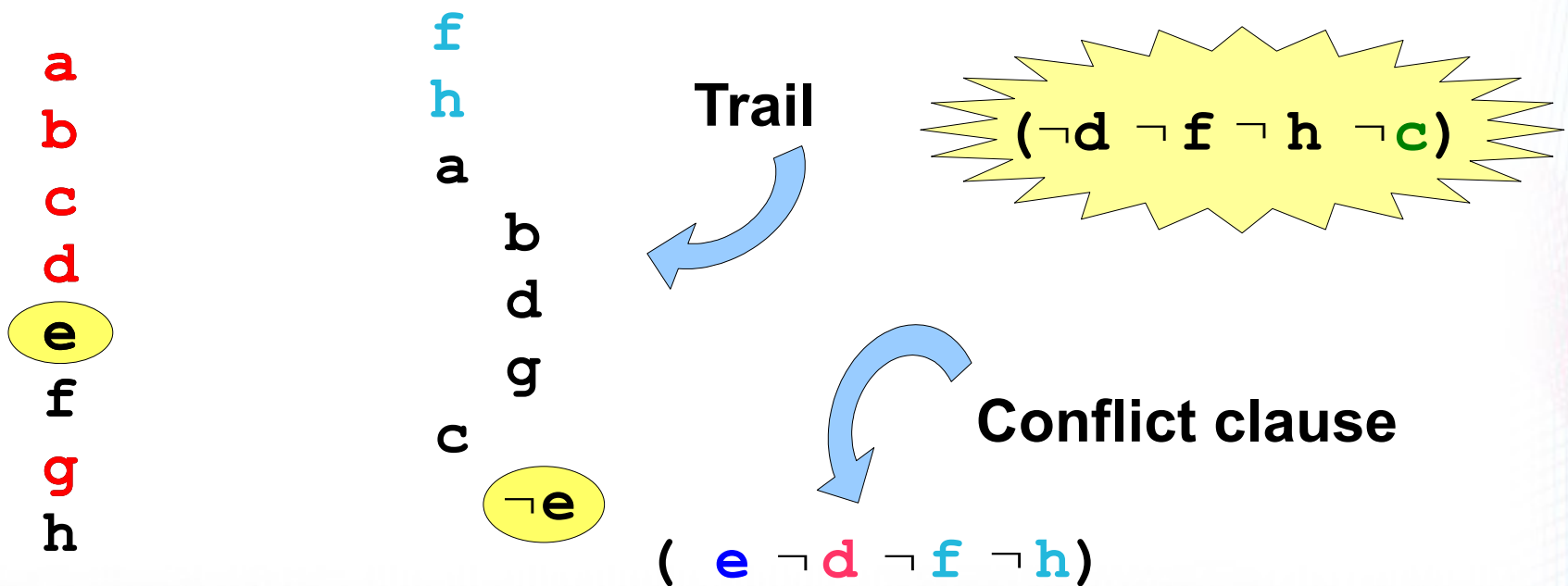
- For better clauses, want an implication graph.
- How to generate it from existing assignment I?
  - CDLS: “simulate UP until it first deviates from I”





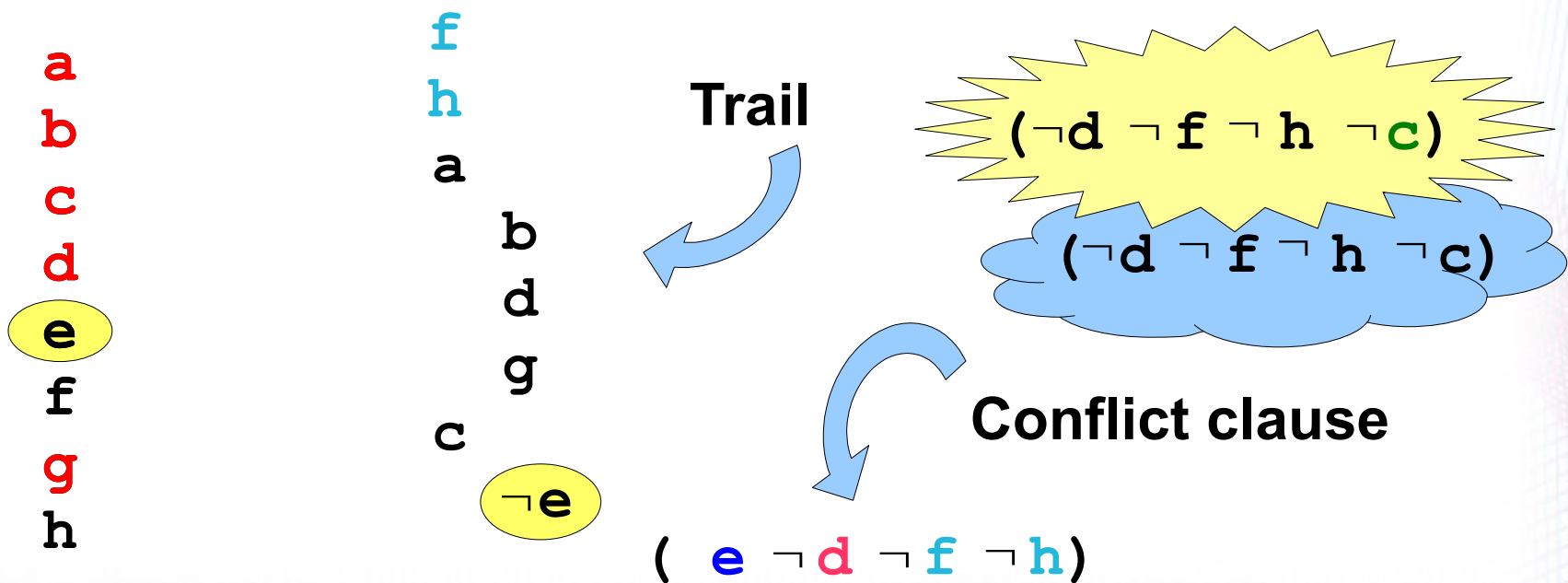
# Local Search

- For better clauses, want an implication graph.
- How to generate it from existing assignment I?
  - CDLS: “simulate UP until it first deviates from I”



# Local Search

- For better clauses, want an implication graph.
- How to generate it from existing assignment I?
  - CDLS: “simulate UP until it first deviates from I”



# Local Search

- Problem: this is not a real conflict.
  - A SAT solver would not have learned here.

a  
b  
c  
d  
e  
f  
g  
h

a  
b  
d  
g  
c  
¬e

# Local Search

- Problem: this is not a real conflict.
  - A SAT solver would not have learned here.
- You cannot “create” a learnable conflict from an arbitrary assignment

a  
b  
c  
d  
e  
f  
g  
h

a  
b  
d  
g  
c  
¬e

# “Unlearnable” assignment

(a, b)  
(c, d)  
( $\neg$ a, c)  
( $\neg$ b, d)  
( $\neg$ c, a)  
( $\neg$ d, b)

$\neg$ a  $\neg$ b  $\neg$ c  $\neg$ d

# “Unlearnable” assignment

(a, b)

(c, d)

( $\neg a$ , c)

( $\neg b$ , d)

( $\neg c$ , a)

( $\neg d$ , b)

$\neg a \quad \neg b \quad \neg c \quad \neg d$

$\neg a$

# “Unlearnable” assignment

(a, b)

(c, d)

( $\neg a$ , c)

( $\neg b$ , d)

( $\neg c$ , a)

( $\neg d$ , b)

$\neg a \quad \neg b \quad \neg c \quad \neg d$

$\neg a$

$\neg c$

b

# “Unlearnable” assignment

(a, b)

(c, d)

( $\neg a$ , c)

( $\neg b$ , d)

( $\neg c$ , a)

( $\neg d$ , b)

$\neg a \quad \neg b \quad \neg c \quad \neg d$

$\neg a$

$\neg c$

**b**



# “Unlearnable” assignment

(a, b)

(c, d)

( $\neg a$ , c)

( $\neg b$ , d)

( $\neg c$ , a)

( $\neg d$ , b)

$\neg a$   $\neg b$   $\neg c$   $\neg d$

$\neg a$

$\neg b$

$\neg c$

$\neg d$

$\neg c$

$\neg d$

$\neg a$

$\neg b$

b

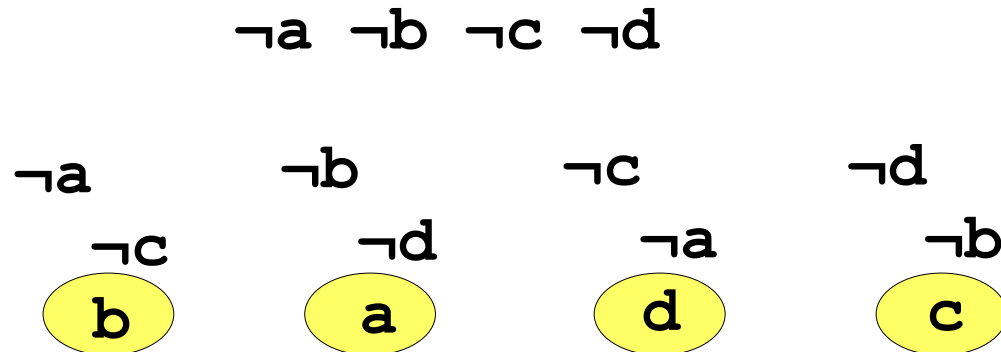
a

d

c

# “Unlearnable” assignment

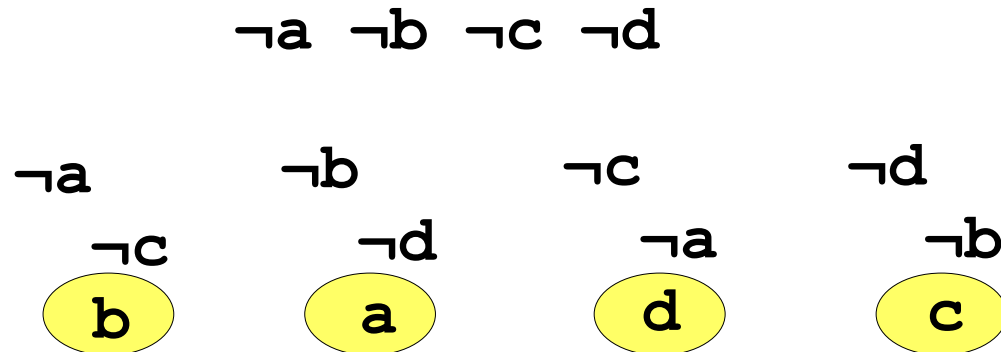
(a, b)  
(c, d)  
( $\neg a$ , c)  
( $\neg b$ , d)  
( $\neg c$ , a)  
( $\neg d$ , b)



Can we go around this limitation?

# “Unlearnable” assignment

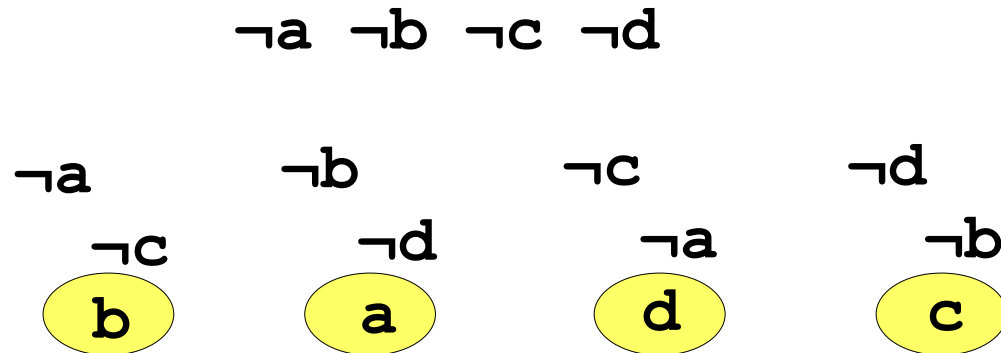
(a, b)  
(c, d)  
( $\neg a$ , c)  
( $\neg b$ , d)  
( $\neg c$ , a)  
( $\neg d$ , b)



Can we go around this limitation?  
• Allow new values?

# “Unlearnable” assignment

(a, b)  
(c, d)  
( $\neg a$ , c)  
( $\neg b$ , d)  
( $\neg c$ , a)  
( $\neg d$ , b)



Can we go around this limitation?

- Allow new values?
- Ignore unneeded implications?

# “Unlearnable” assignment

(a, b)

(c, d)

( $\neg a$ , c)

( $\neg b$ , d)

( $\neg c$ , a)

( $\neg d$ , b)

$\neg a$   $\neg b$   $\neg c$   $\neg d$

$\neg a$

$\neg b$

$\neg c$

$\neg d$

$\neg c$

$\neg d$

$\neg a$

$\neg b$

b

a

d

c

$\neg b$

$\neg d$

a

# “Unlearnable” assignment

● (a, b)

● (c, d)

( $\neg a$ , c)

( $\neg b$ , d)

( $\neg c$ , a)

( $\neg d$ , b)

$\neg a$   $\neg b$   $\neg c$   $\neg d$

$\neg a$

$\neg b$

$\neg c$

$\neg d$

$\neg c$

$\neg d$

$\neg a$

$\neg b$

b

a

d

c

$\neg b$

$\neg d$

a

# “Unlearnable” assignment

● (a, b)

● (c, d)

( $\neg a$ , c)

( $\neg b$ , d)

( $\neg c$ , a)

( $\neg d$ , b)

$\neg a$   $\neg b$   $\neg c$   $\neg d$

$\neg a$

$\neg b$

$\neg c$

$\neg d$

$\neg c$

$\neg d$

$\neg a$

$\neg b$

b

a

d

c

$\neg b$

$\neg d$

a

- So: the problem is in the heuristic.
- We don't want “unlearnable” assignments to be a local minima
- *Note:* above assignment is a local minima for clause counting

# choosing variables to flip through CDCL

- Inspired by intuition from CDCL solvers
- Uses a base heuristic for variable ordering  
(For eg, VSIDS)
- Guarantees a learnable clause
- Makes the local search solver behave exactly as a CDCL solver



# CDCL Local Search

## `pickVar(I)`

- Order  $I$  in a UP-compatible order
  - implied variables have to appear as soon as possible after their reasons
  - (see the paper for more precise definition)
- Pick a false clause  $C$  that becomes unit earliest
  - It would have implied some variable  $v$
- If  $\neg v$  is implied earlier, have a real conflict.
  - learn a clause from  $C$  using the above ordering
- Otherwise, flip  $v$ .

# Exploiting the insight

- A more efficient way to select variables to flip
  - Vector or vectors instead of a trail?
  - Completely different implementation?
- More freedom
  - Generating other empowering clauses and/or multiple ones from the same assignment?

# Learning multiple clauses at once

- Preliminary work
  - currently no way to estimate which are “good” clauses in this context
  - doesn't provide empowerment guarantees
- First conflict clause at every decision level
  - if  $\alpha$  does not derives any failed implications, “asserting” clause  $(\alpha \rightarrow y)$  is empowering

# Learning multiple clauses at once

Number of SAT11 problems solved within 1000s: **All**, **True**, **False** instances

Family	Minisat	C_1	C_5	C_10	C_100	C_1000	C_All
	A S U	A S U	A S U	A S U	A S U	A S U	A S U
fuhs (34)	10 <b>9</b> 1	10 8 2	9 8 1	9 8 1	10 7 <b>3</b>	10 8 2	7 7 0
manthey (9)	3 <b>3</b> 0	2 2 0	2 2 0	3 <b>3</b> 0	3 <b>3</b> 0	1 1 0	0 0 0
jarvisalo (47)	24 8 <b>16</b>	24 8 <b>16</b>	24 9 15	24 <b>10</b> 14	25 9 <b>16</b>	17 6 11	15 6 9
leberre (17)	11 4 7	13 <b>6</b> 7	14 <b>6</b> 8	13 <b>6</b> 7	13 <b>6</b> 7	12 5 7	7 1 6
rintanen (30)	9 <b>7</b> 2	8 5 <b>3</b>	7 4 <b>3</b>	8 5 <b>3</b>	8 5 <b>3</b>	2 1 1	1 0 1
kullmann (13)	2 2 0	3 3 0	3 3 0	2 2 0	<b>4</b> <b>4</b> 0	3 3 0	3 3 0
<b>Total (150)</b>	59 33 26	60 32 28	59 32 27	59 <b>34</b> 25	<b>63</b> <b>34</b> <b>29</b>	45 24 21	33 17 16

- **C\_All** learns all clauses all the time
- **C\_n** learns all clauses n times every restart, standard learning at other times



# Future work

- A more efficient way to calculate the heuristic
- More freedom
  - Generating other empowering clauses and/or multiple ones from the same assignment?
- Relaxing the restrictions in QBF?
- Other local search heuristics that guarantee “real” conflicts?
- Local search “base” heuristics?

# Conclusion

- Reformulated CDCL algorithm as local search
- The trail is simply an efficient way for computing the heuristic
- New view to be explored, and more flexibility to be investigated
  - learning other clauses?
  - better ways of computing the heuristic?
  - flexibility for QBF?