# SAT/SMT Solvers and Applications

Vijay Ganesh
University of Waterloo
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### The Goals of this Course

### Introduction to SAT/SMT Solvers

- What are constraint solvers (e.g., Boolean SAT and SMT solvers)?
- Why should you care?
- Theoretical aspects (e.g., proof theoretic treatment of modern SAT algorithm)
- Practical aspects (e.g., Important SAT/SMT solver heuristics)

### **Applications**

- Symbolic execution and solver-based automated bug finding
- Solver-based program analysis/synthesis
- Solver-based model-checking and theorem provers
- Debugging and equivalence-checking tools
- Market Applications in Al
- Solvers and computer security
- Solver-based modeling and requirements analysis

### Goals of this Course Lecture Schedule

- Modern CDCL SAT solvers: core ideas (VG)
- Modern SMT Solvers: core ideas (VG)
- MiniSAT: Anatomy of a modern CDCL SAT solver (VG and students)
- Symbolic execution and solver-based automated bug finding (VG and students)
- Solver-based program analysis/synthesis (Frank Tip)
- Solver-based model-checking and theorem provers (Shoham Ben-David)
- Marging and equivalence-checking tools (VG and students)
- Mark Applications in AI (Peter Van Beek)
- Solver-based modeling and requirements analysis (Czarnecki and Rayside)
- Solvers and computer security (Mahesh Tripunitara)
- Solvers and programming languages (VG and students)

### What is a Constraint Solver?

### Engineer/Mathematician's point of vew

- M "method" that takes as input a math formula, and produces a solution
- **Examples:** solving linear equations over the reals, polynomials, quadratic, Boolean logic,...
- **M** Computing zeros of a polynomial

### Theoretical computer scientist/logician's point of view

- M Computer program called as a satisfiability procedure that solves a specific kind of decision problem, namely, the SAT problem
- The input formula is in a specified logic (e.g., Boolean, first-order, reals, integers,...)
- Output of a satisfiability procedure
  - UNSAT, if input has no satisfying assignments
  - SAT, otherwise

### One Slide History of Constraint Solving Methods

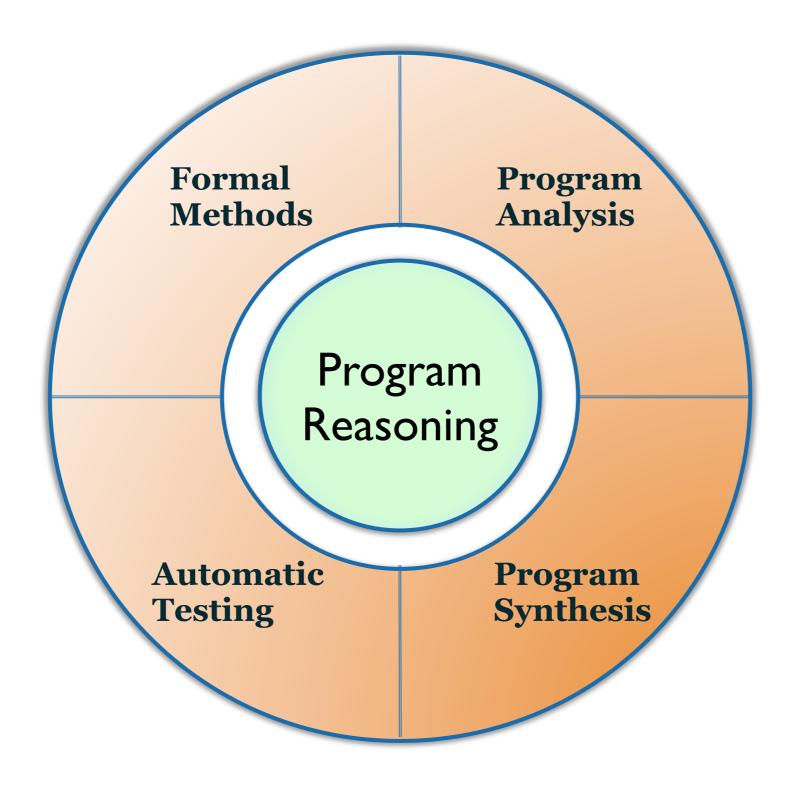
### Before modern conception of logic (Before Boole and Frege)

- From Babylon to late 1800's: Huge amount of work on methods to solve (find roots of) polynomials over reals, integers,...
- System of linear equations over the reals (Chinese methods, Cramer's method, Gauss elimination)
- These methods were typically not complete (e.g., worked for a special class of polynomials)

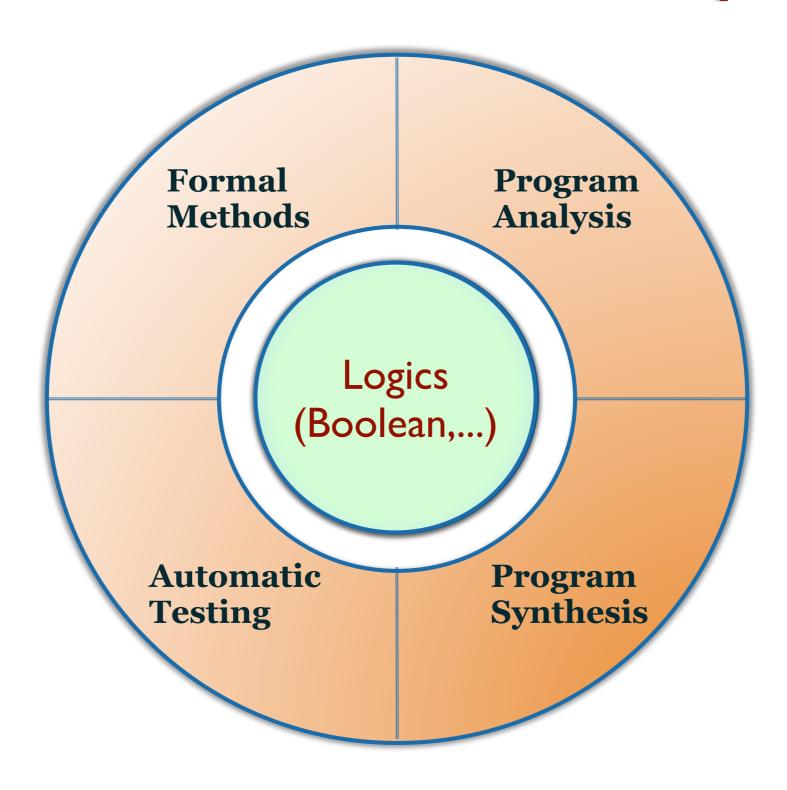
### After modern conception of logic

- Systems of linear inequalities over the integers are solvable (Presburger, 1927)
- Peano arithmetic is undecidable (hence, not solvable) (Godel, 1931)
- First-order logic is undecidable (hence, not solvable) (Turing, 1936. Church, 1937)
- A exponential-time algorithm for Boolean SAT problem (Davis, Putnam, Loveland, Loggeman in 1962)
- Systems of Diophantine equations are not solvable (Matiyasevich. 1970)
- Moolean SAT problem is NP-complete (Cook 1971)
- Many efficient, scalable SAT procedures since 1971 for a variety of mathematical theories

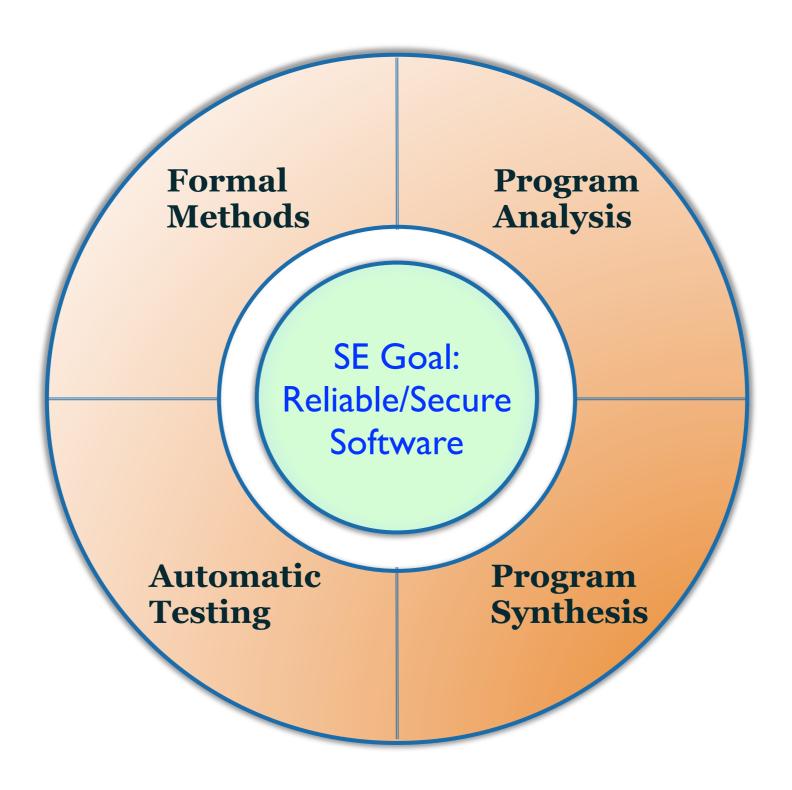
# Foundation of Sofware Engineering Logic Abstractions of Computation



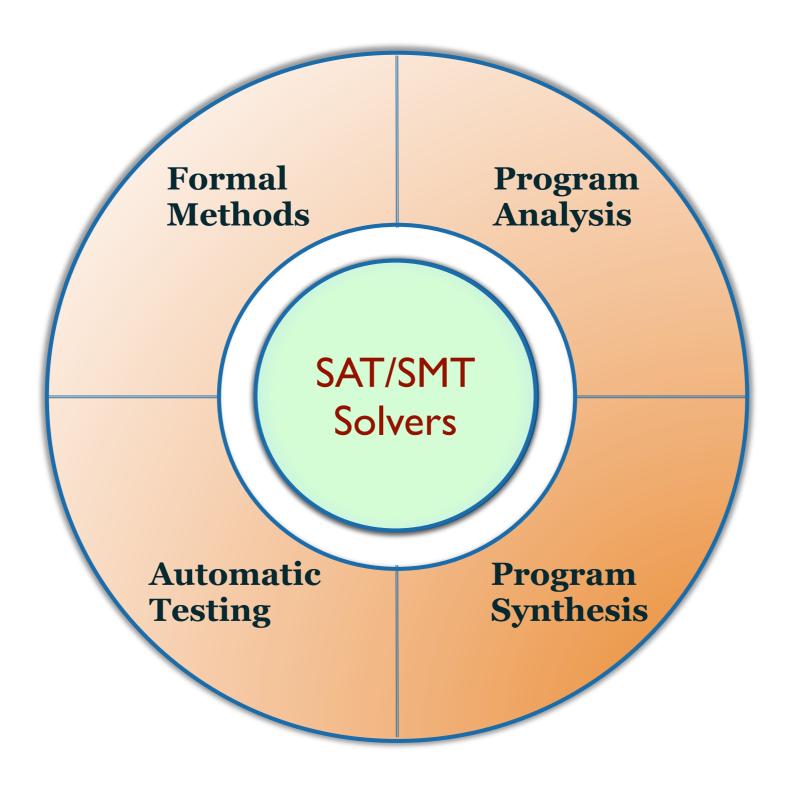
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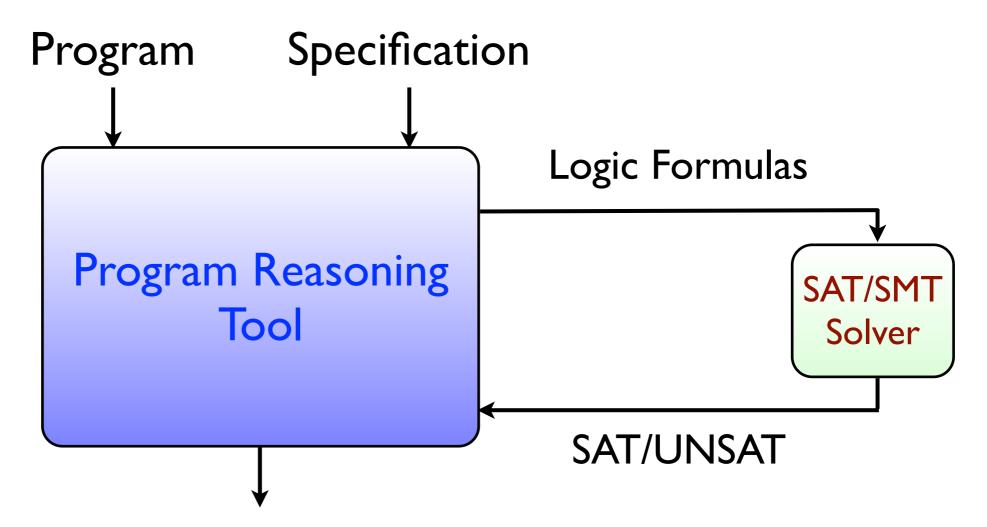
# Software Engineering & SAT/SMT Solvers An Indispensable Tactic for Any Strategy



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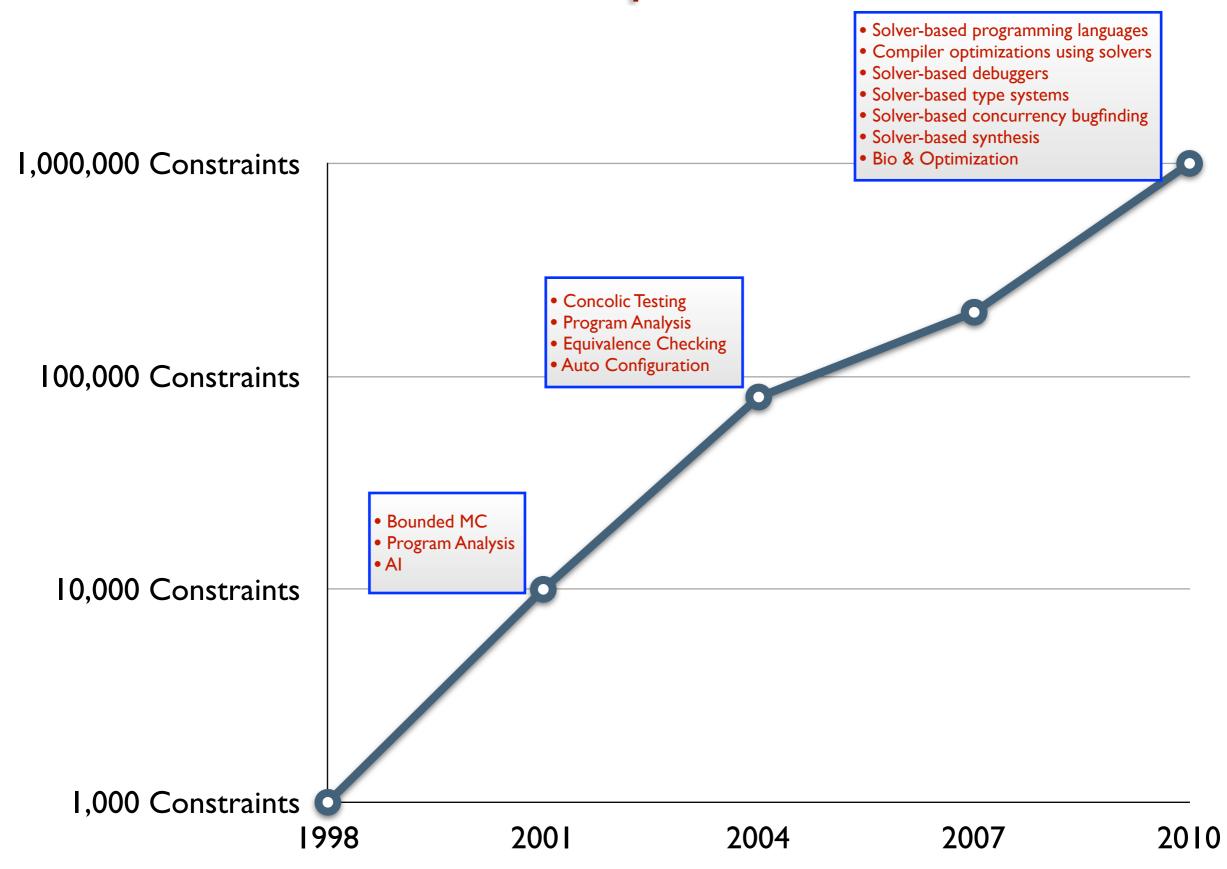


# Software Engineering using Solvers Engineering, Usability, Novelty



Program is Correct? or Generate Counterexamples (Test cases)

### SAT/SMT Solver Research Story A 1000x Improvement



### Why Should You Care?

### SAT/SMT solver user

- Use solver as a black-box
- More importantly, solver algorithms are influencing algorithms in other areas
- Synthesis: Sketching by Armando Solar-Lezama uses SAT techniqes
- Manalysis: Combining static and dynamic analysis has a flavor of the SAT algorithm
- Model-checking: The IC3 algorithm integrates SAT deeply into the model-checker

### Some SAT/SMT solvers users at Waterloo

- Meson, Tripunitara, Garg are using programmatic SAT for hardware security
- Krzysztof Czarnecki's group is using solvers for auto-configuration
- Torek Rayside's group is using solvers for software modelling through Alloy
- Frank Tip's group is using solvers for analysis
- Peter Van Beek's group works on CSPs, closely related to SAT
- Venkat Raman is working on complexity-theoretic aspects of the SAT problem
- Lin Tan's group is looking into symbolic-execution/solver-based bug finding

### Brief overview of relevant Logic Concepts

What is a Logic?

What is a mathematical theory?

Notions of models, truth and proof

What is the connection between truth and proof?

What are the satisfiability and validity problems?

What is a decision procedure?

What is a satisfiability procedure?

What is the connection between satisfiability, validity and proof?

What is meant by soundness and completeness?

### Logic, model, truth, assignments

- Study of valid modes of reasoning (inductive, deductive, ...)
- Formal language (e.g., Boolean logic, first-order logic,...)
- Rules for constructing well-formed formulas
- An associated proof system (axioms, inference rules,...)
- Model
  - Interpretation of connectives, functions, predicates over a domain
  - True, false
  - Assignment: Mapping of variables to elements of the domain

### The SAT/SMT Problem



- Rich logics (Modular arithmetic, Arrays, Strings,...)
- NP-complete, PSPACE-complete,...
- Practical, scalable, usable, automatic
- Enable novel software reliability approaches

### The SAT/SMT Problem



- Closely related to the Validity Problem
- Soundness, completeness, termination
- Connecting model theory and proof theory

### Lecture Outline

### Points already covered

- Motivation for SAT/SMT solvers in software engineering
- ☑ High-level description of the SAT/SMT problem & logics
- Margine Defined logic, models, truth, proofs, SAT procedure, soundness, completeness

### Rest of the lecture

- Modern CDCL SAT solver architecture & techniques
- SAT/SMT-based applications
- Future of SAT/SMT solvers
- Some history (who, when,...) and references sprinkled throughout the talk
- Non-CDCL SAT techniques

# The Boolean SAT Problem Basic Definitions and Format

A **literal** p is a Boolean variable x or its negation  $\neg x$ .

A clause C is a disjunction of literals:  $x_2 \vee \neg x_{41} \vee x_{15}$ 

A CNF is a conjunction of clauses:  $(x_2 \lor \neg x_1 \lor x_5) \land (x_6 \lor \neg x_2) \land (x_3 \lor \neg x_4 \lor \neg x_6)$ 

All Boolean formulas assumed to be in CNF

Assignment is a mapping (binding) from variables to Boolean values (True, False).

A unit clause C is a clause with a single unbound literal

#### The **SAT-problem** is:

Find an assignment s.t. each input clause has a true literal (aka input formula has a solution or is SAT) OR establish input formula has no solution (aka input formula is UNSAT)

The Input formula is represented in **DIMACS Format:** 

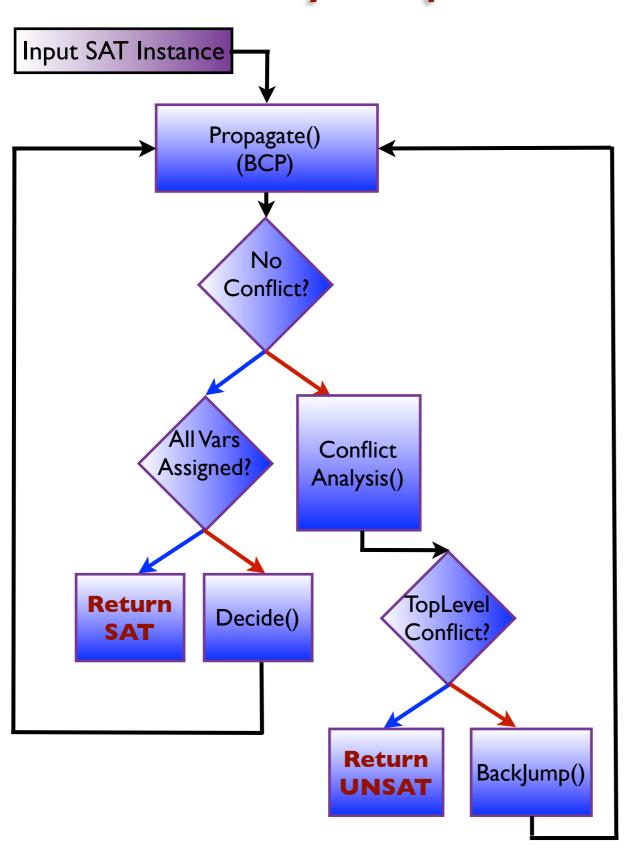
```
c DIMACS
p cnf 6 3
2 -1 5 0
6 -2 0
3 -4 -6 0
```

### DPLL SAT Solver Architecture The Basic Solver

```
DPLL(\Theta_{cnf}, assign) {
   Propagate unit clauses;
   if "conflict": return FALSE;
   if "complete assign": return TRUE;
   "pick decision variable x";
   return
          DPLL(\Theta_{cnf} | x=0, assign[x=0])
       || DPLL(\Theta_{cnf}|_{x=1}, assign[x=1]);
```

- Propagate (Boolean Constant Propagation):
  - Propagate inferences due to unit clauses
  - Most time in solving goes into this
- Detect Conflict:
  - Conflict: partial assignment is not satisfying
- Decide (Branch):
  - Choose a variable & assign some value
- Backtracking:
  - Implicitly done by the recursion

### Modern CDCL SAT Solver Architecture Key Steps and Data-structures



#### Key steps

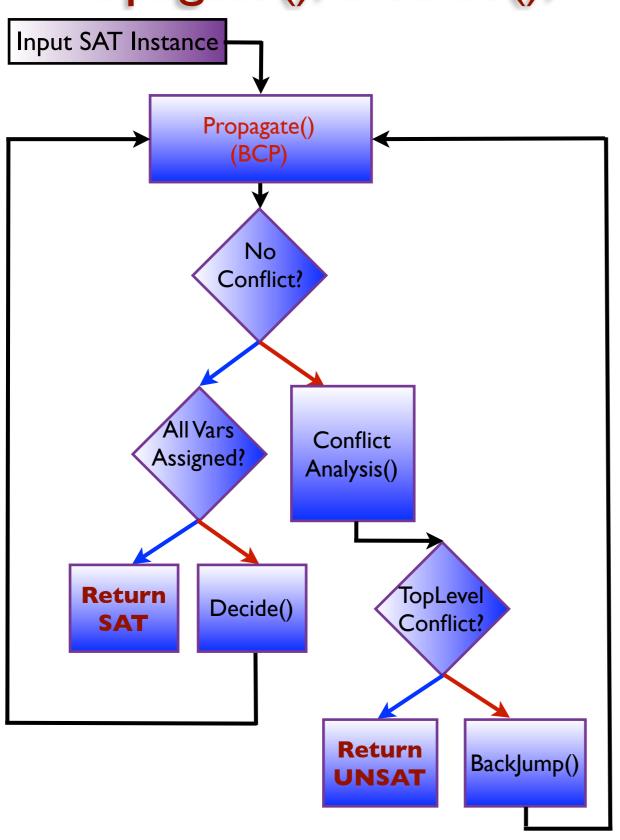
- Decide()
- Propagate()(BCP: Boolean constraint propagation)
- Conflict analysis and learning()
- Backjump()
- Forget()
- Restart()

#### CDCL: Conflict-Driven Clause-Learning

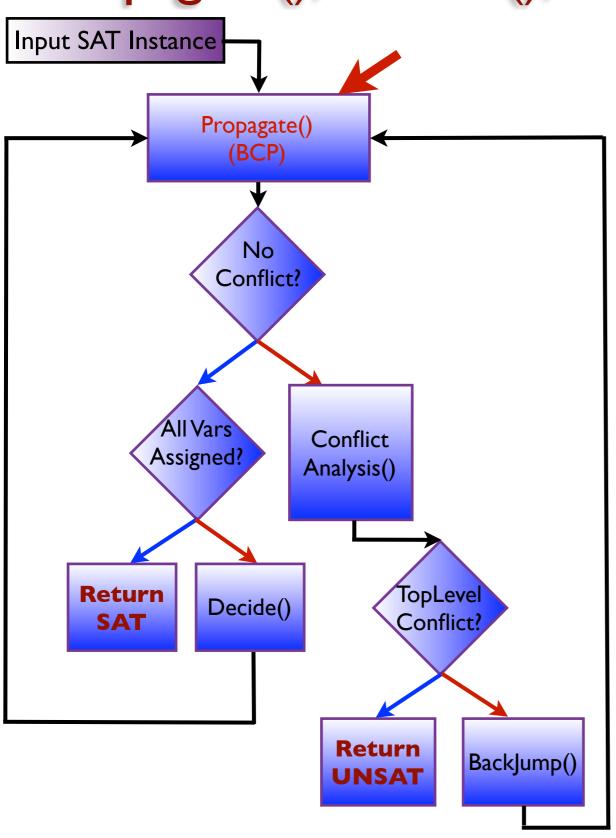
- Conflict analysis is a key step
- Results in learning a conflict clause
- Prunes the search space

#### Key data-structures (State):

- Stack or trail of partial assignments (AT)
- Input clause database
- Conflict clause database
- Conflict graph
- Decision level (DL) of a variable



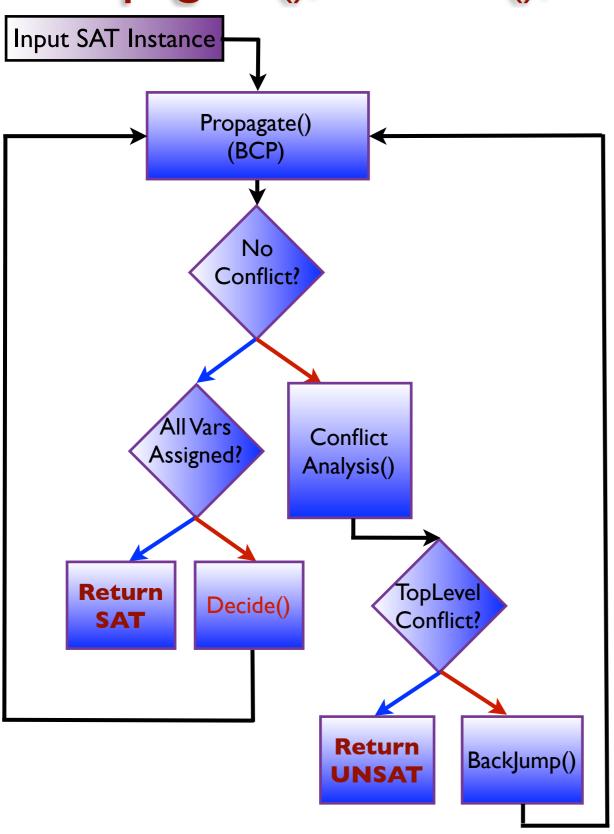
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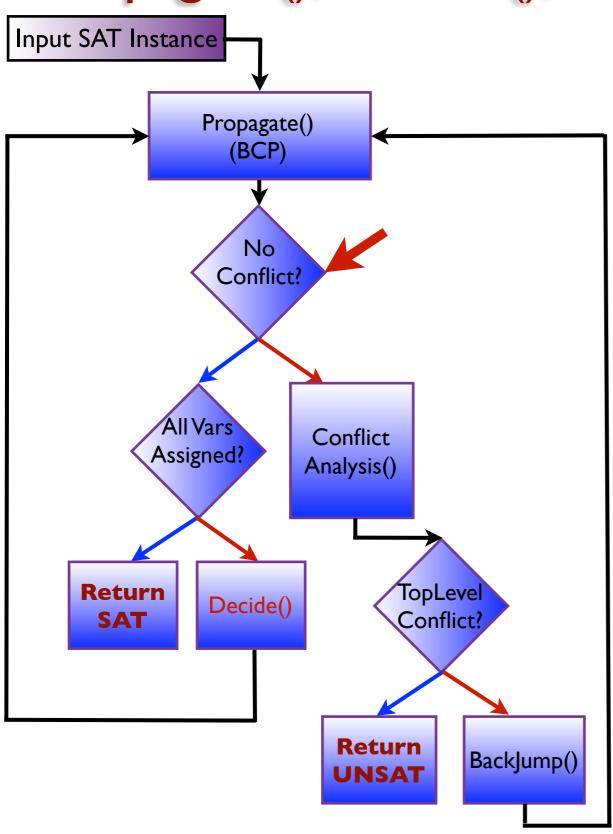
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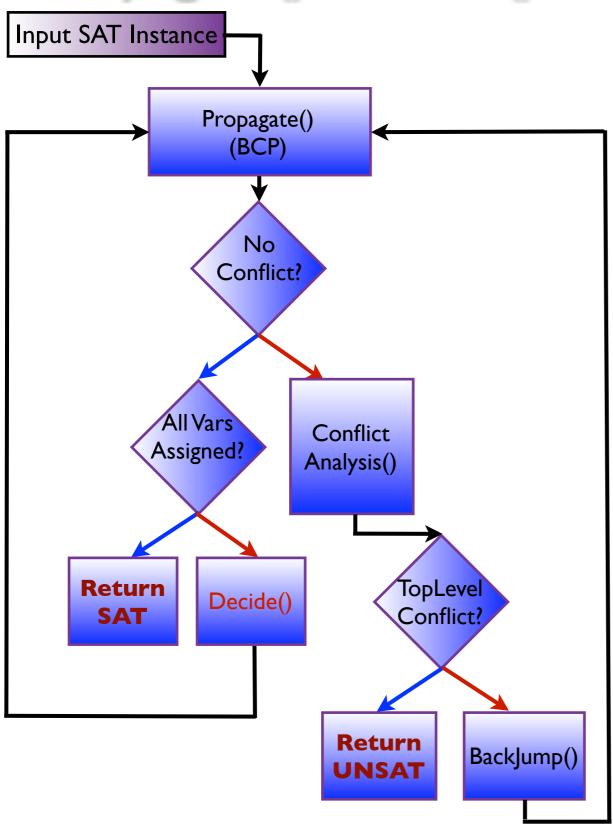
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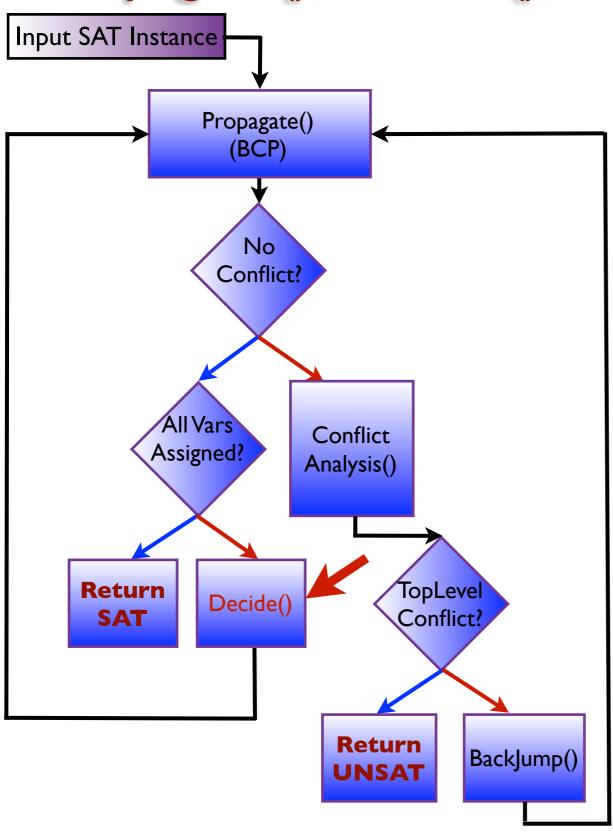
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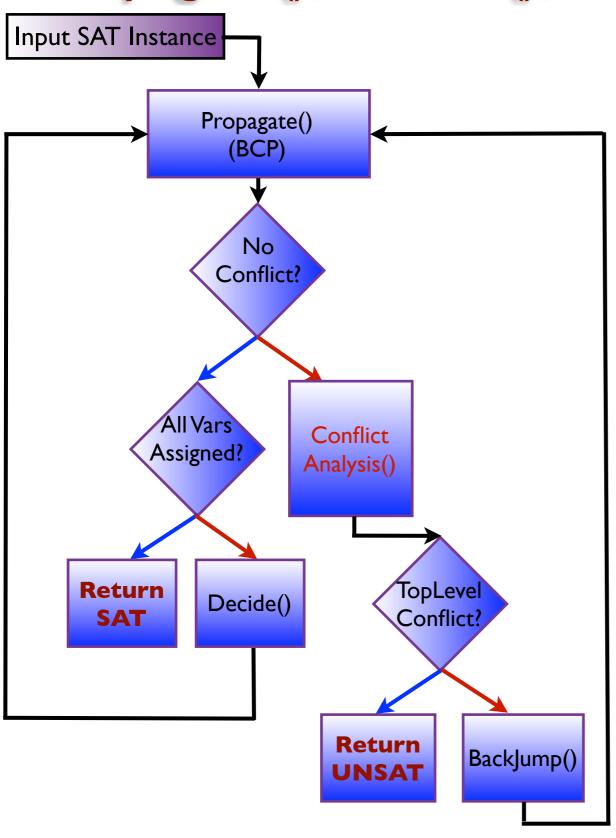
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  - Imposes dynamic variable order
  - Decision Level (DL): variable ⇒ natural number



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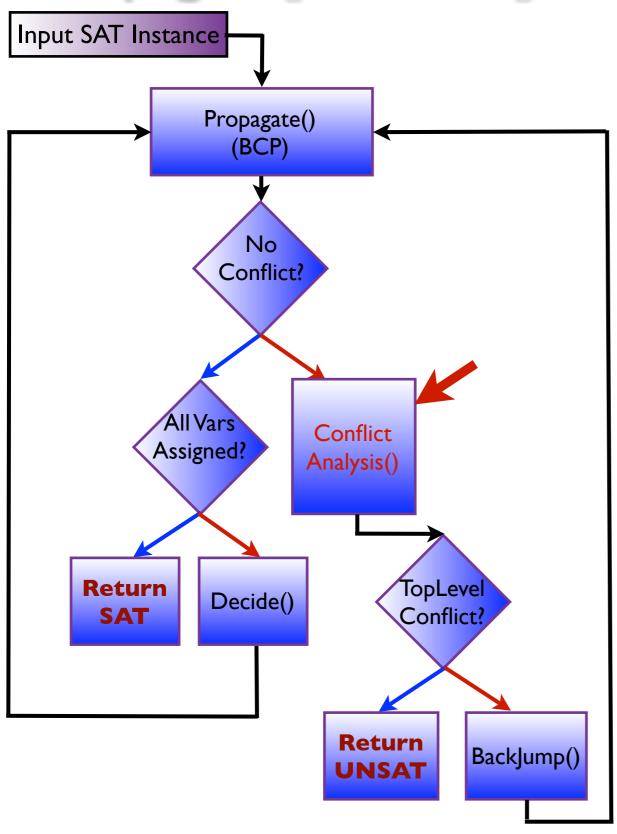


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- Conflict analysis and clause learning:
  - Compute assignments that lead to conflict (analysis)
  - Construct conflict clause blocks the non-satisfying & a large set of other 'no-good' assignments (learning)
  - Marques-Silva & Sakallah (1996)



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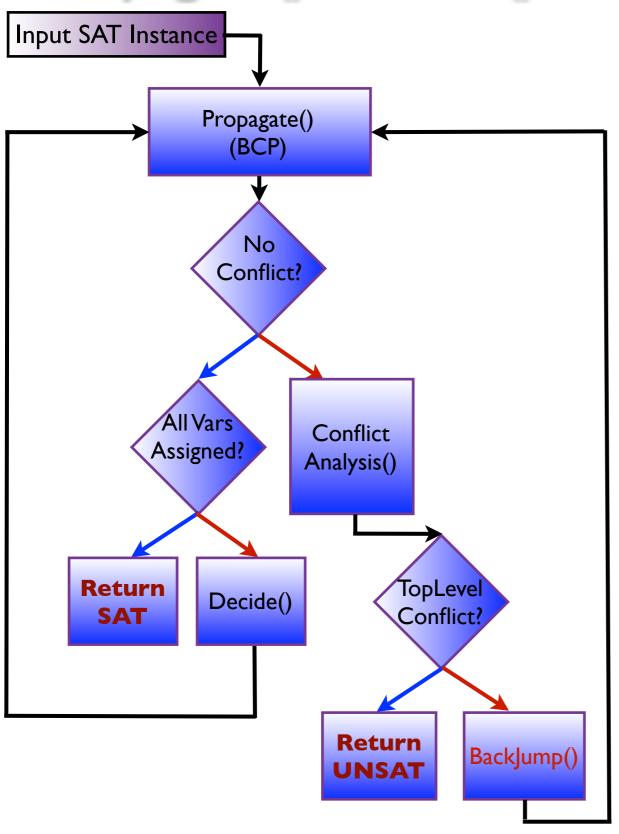
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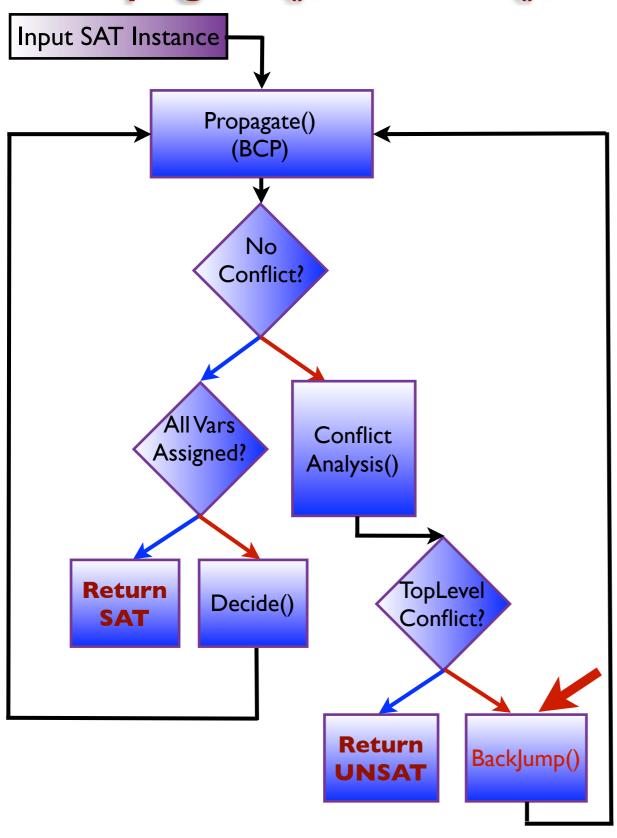
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#### • Conflict-driven Backlump:

- Undo the decision(s) that caused no-good assignment
- Assign 'decision variables' different values
- Go back several decision levels
- Backjump: Marques-Silva, Sakallah (1999)
- Backtrack: Davis, Putnam, Loveland, Logemann (1962)



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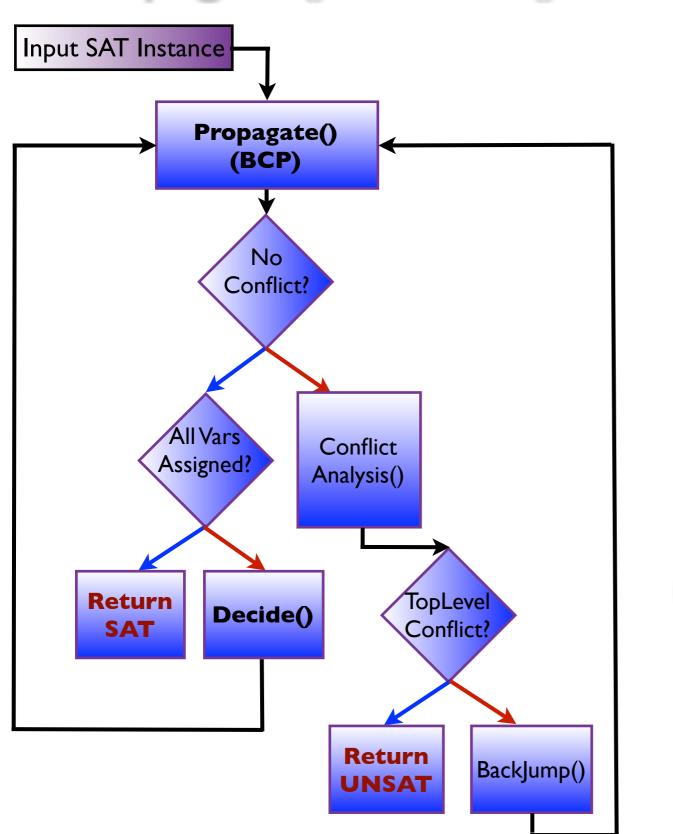
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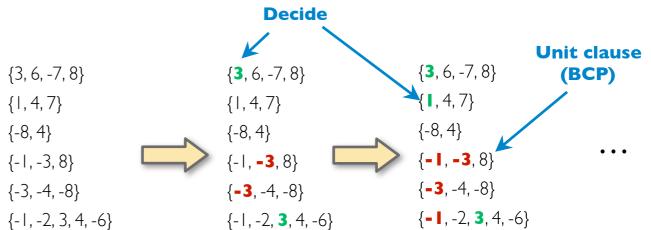
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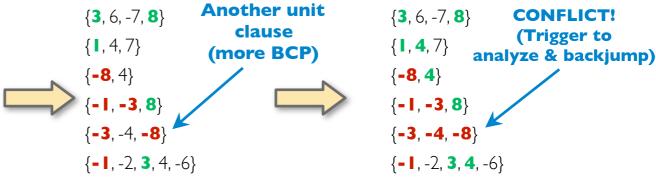
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### Modern CDCL SAT Solver Architecture

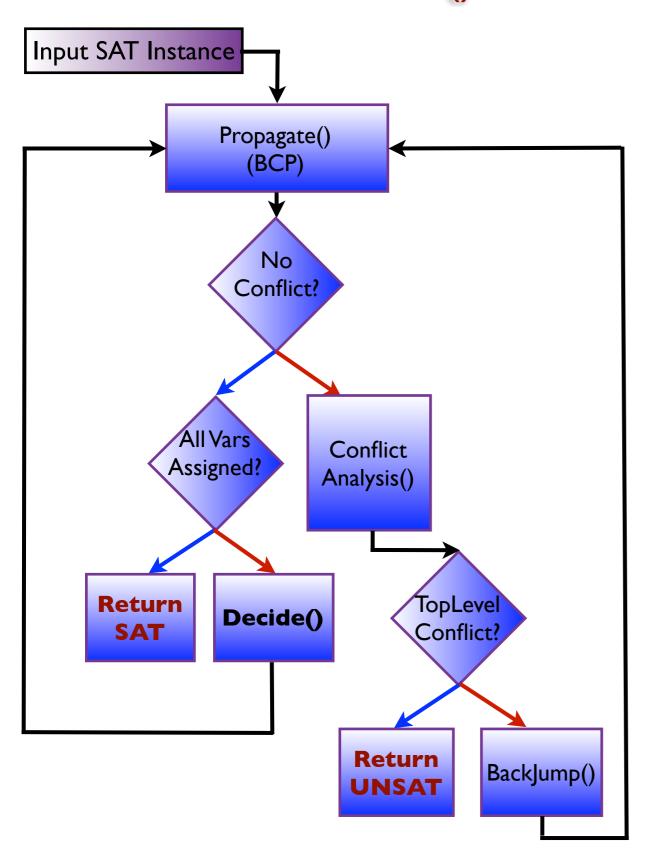
Propagate(), Decide(), Analyze/Learn(), BackJump()





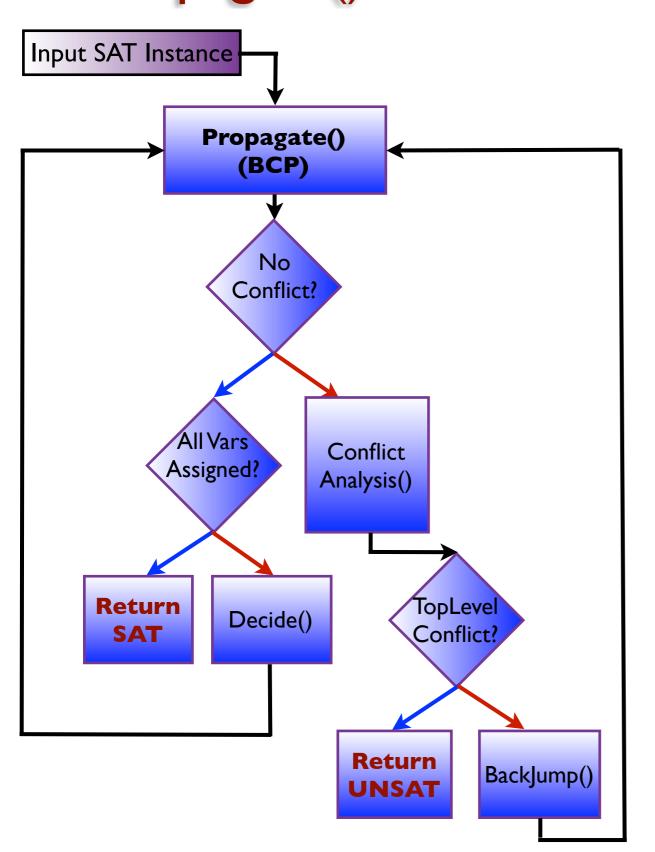


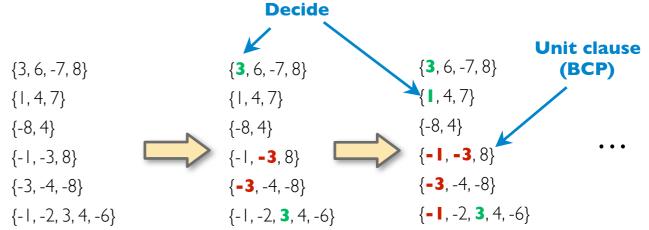
### Modern CDCL SAT Solver Architecture Decide() Details: VSIDS Heuristic



- Decide() or Branching():
  - Choose a variable & assign some value (decision)
  - Imposes dynamic variable order (Malik et al. 2001)
- How to choose a variable:
  - VSIDS heuristics
  - Each variable has an activity
  - Activity is bumped additively, if variable occurs in conflict clause
  - Activity of all variables is decayed by multiplying by const < 1</li>
  - Next decision variable is the variable with highest activity
  - Over time, truly important variables get high activity
  - This is pure magic, and seems to work for many problems

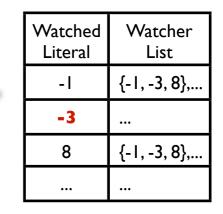
### Modern CDCL SAT Solver Architecture Propagate() Details: Two-watched Literal Scheme





Watched Literal	Watcher List
-1	{-1, -3, 8},
-3	{-1, -3, 8},





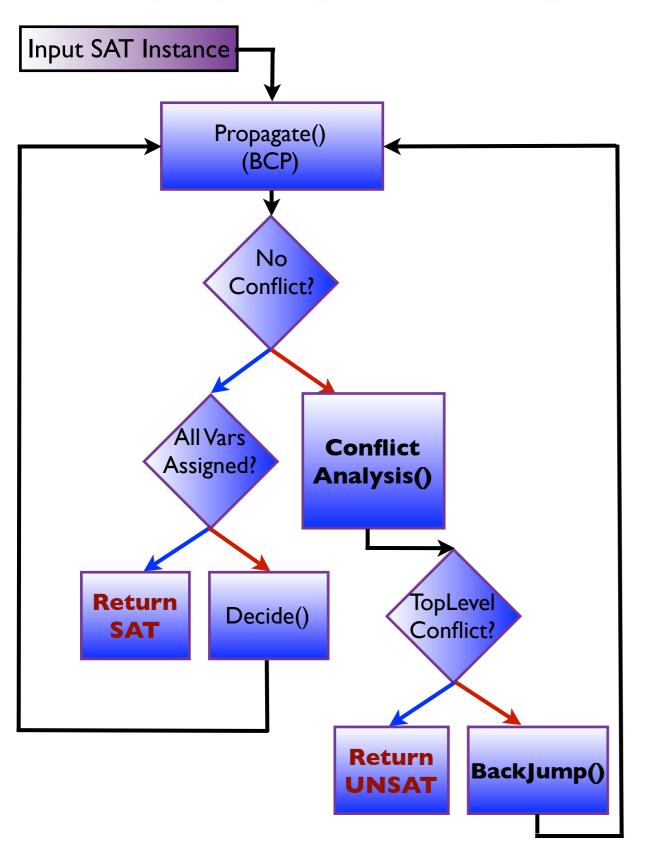


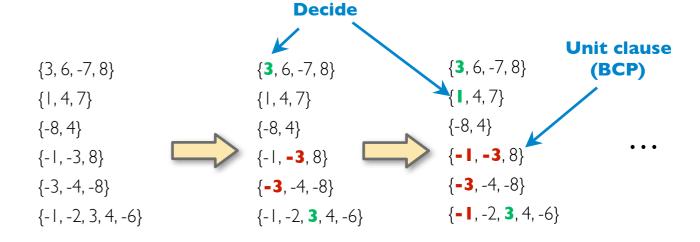


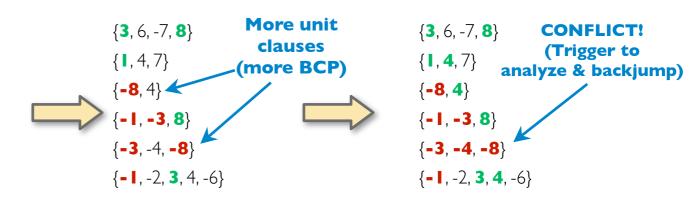
The constraint propagates 8

### Modern CDCL SAT Solver Architecture

### Propagate(), Decide(), Analyze/Learn(), BackJump()



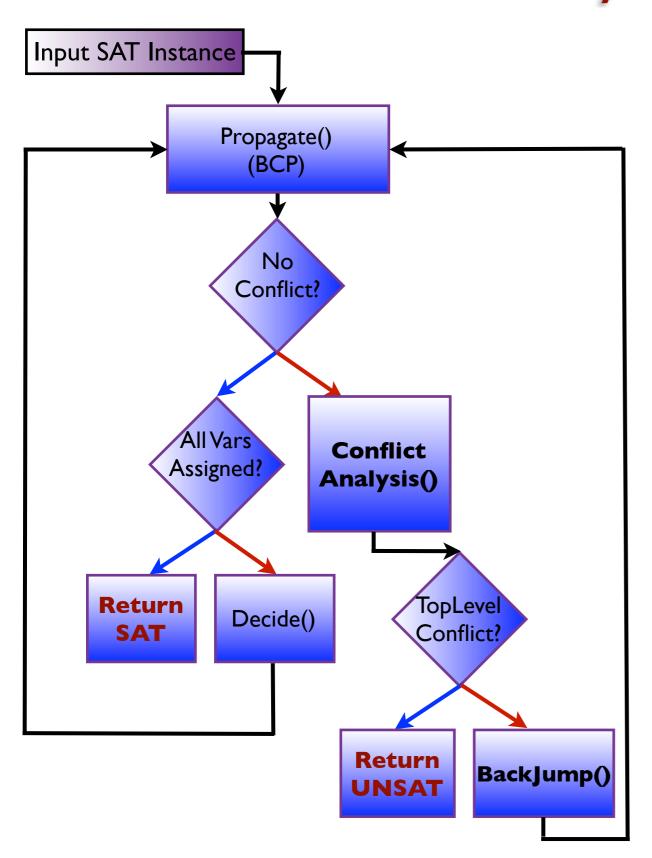




#### Basic Backtracking Search

- Flip the last decision |
- Try setting I to False
- Highly inefficient
- No learning from mistakes

### Modern CDCL SAT Solver Architecture Conflict Analysis/Learn() Details



#### Some Definitions

- Decision Level (DL)
  - Map from Boolean variables in input to natural numbers
  - All unit clauses in input & resultant propagations get DL = 0
  - Every decision var gets a DL in increasing order >= I
  - All propagations due to decision var at DL=x get the DL=x
- Conflict Graph (CG) or Implication Graph
  - Directed Graph that records decisions & propagations
  - Vertices: literals, Edge: unit clauses
- Conflict Clause (CC)
  - Clause returned by Conflict Analysis(), added to conflict DB
  - Implied by the input formula
  - A cut in the CG
  - Prunes the search
- Assignment Trail (AT)
  - A stack of partial assignment to literals, with DL info

# Modern CDCL SAT Solver Architecture Conflict Analysis/Learn() Details: Implication Graph

Current Assignment Trail:  $\{X_9 = 0@1, X_{10} = 0@3, X_{11} = 0@3, X_{12} = 1@2, X_{13} = 1@2, ...\}$ 

Current decision:  $\{X_1 = 1@6\}$ 

#### Clause DB

$$W_1 = (\neg X_1 + X_2)$$

$$W_2 = (\neg X_1 + X_3 + X_9)$$

$$W_3 = (\neg X_2 + \neg X_3 + X_4)$$

$$W_4 = (\neg X_4 + X_5 + X_{10})$$

$$W_5 = (\neg X_4 + X_6 + X_{11})$$

$$W_6 = (\neg X_5 + \neg X_6)$$

$$W_7 = (X_1 + X_7 + \neg X_{12})$$

$$W_8 = (X_1 + X_8)$$

$$W_9 = (\neg X_7 + \neg X_8 + \neg X_{13})$$

$$X_{10} = 0@3$$



$$X_9 = 0@1$$



$$X_{11} = 0@3$$



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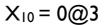
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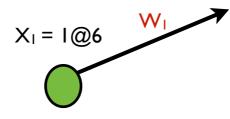
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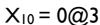
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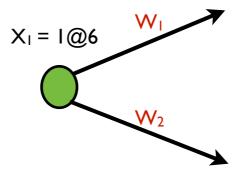
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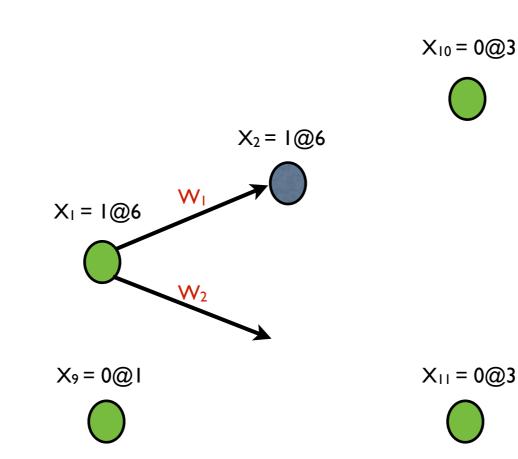
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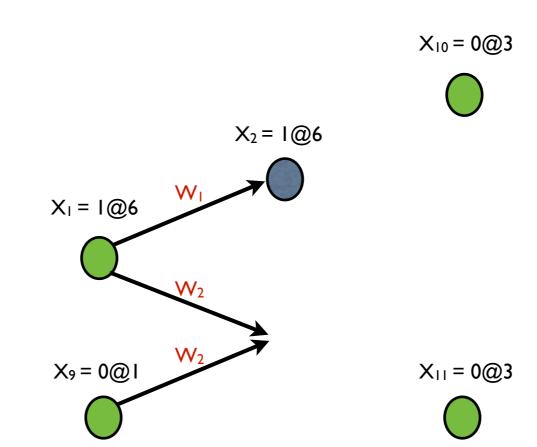
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$$W_9 = (\neg X_7 + \neg X_8 + \neg X_{13})$$



Current Assignment Trail:  $\{X_9 = 0@1, X_{10} = 0@3, X_{11} = 0@3, X_{12} = 1@2, X_{13} = 1@2, ...\}$ 

Current decision:  $\{X_1 = 1@6\}$ 

$$W_1 = (\neg X_1 + X_2)$$

$$W_2 = (\neg X_1 + X_3 + X_9)$$

$$W_3 = (\neg X_2 + \neg X_3 + X_4)$$

$$W_4 = (\neg X_4 + X_5 + X_{10})$$

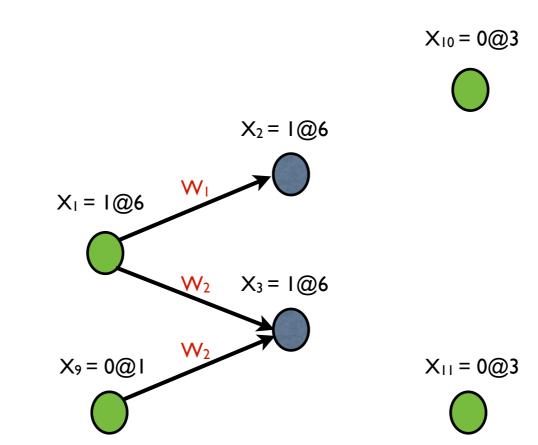
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$$W_6 = (\neg X_5 + \neg X_6)$$

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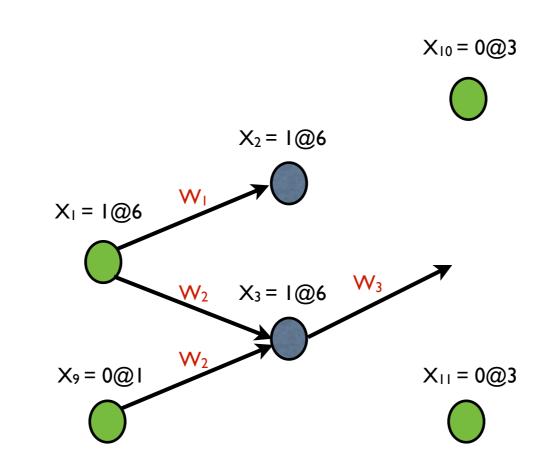
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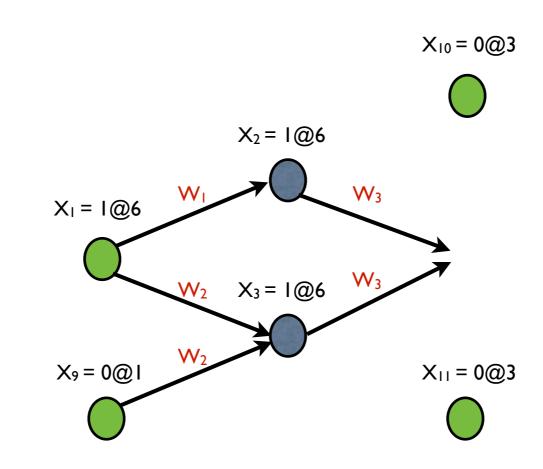
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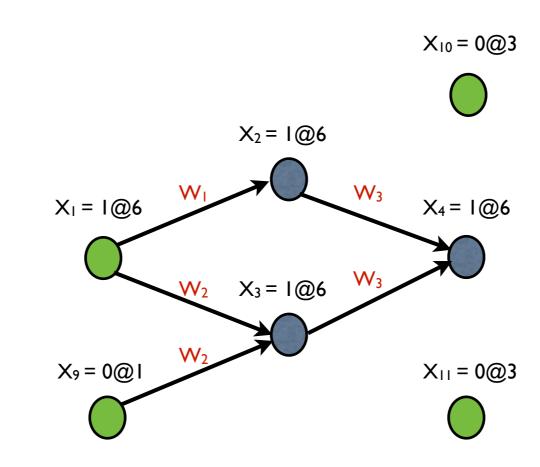
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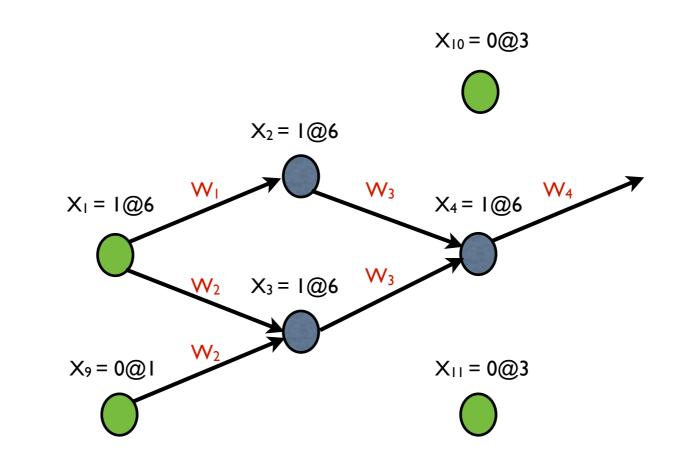
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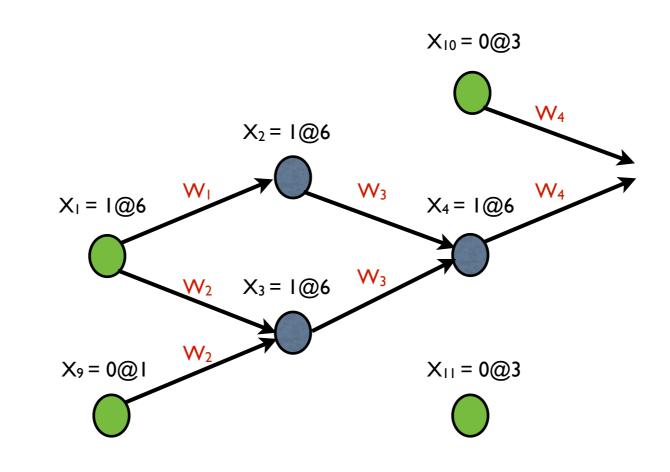
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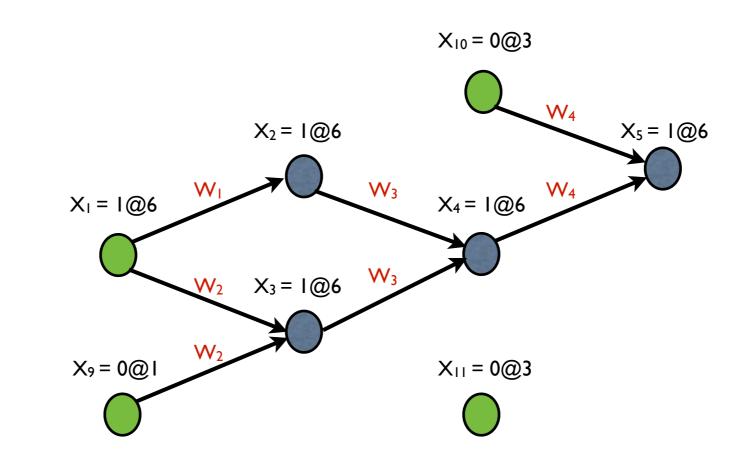
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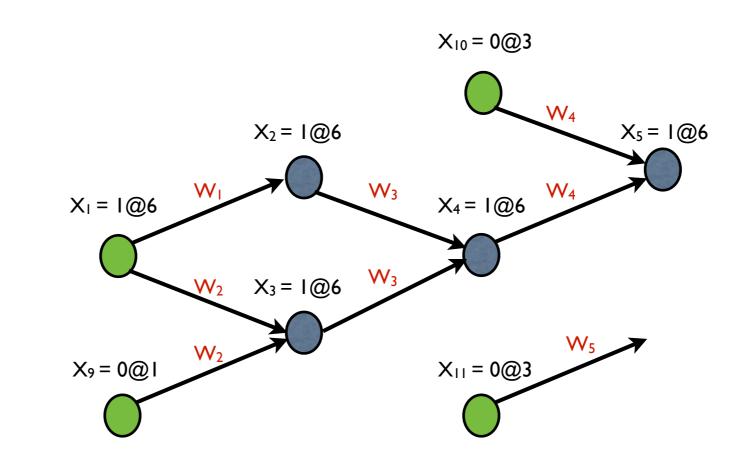
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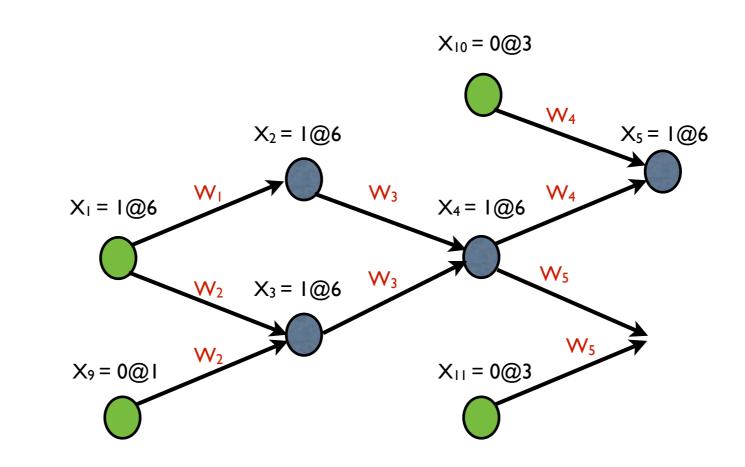
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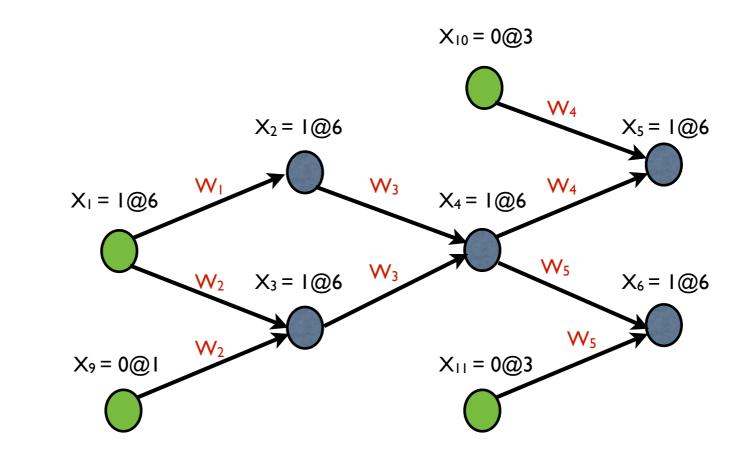
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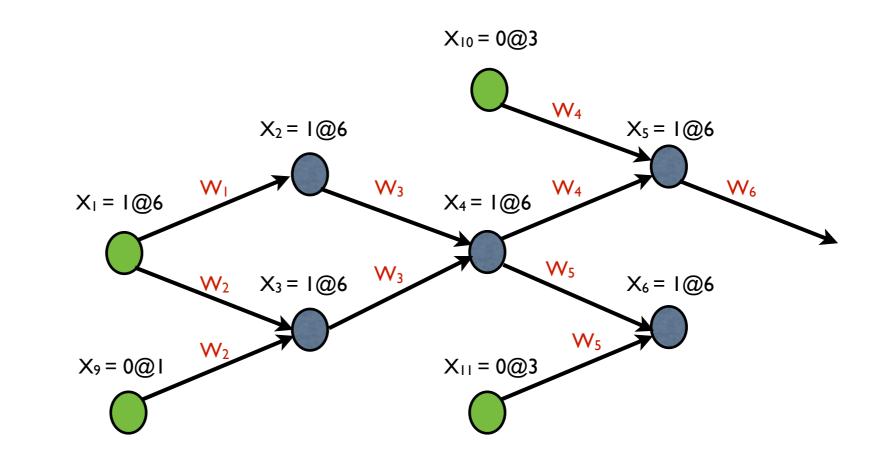
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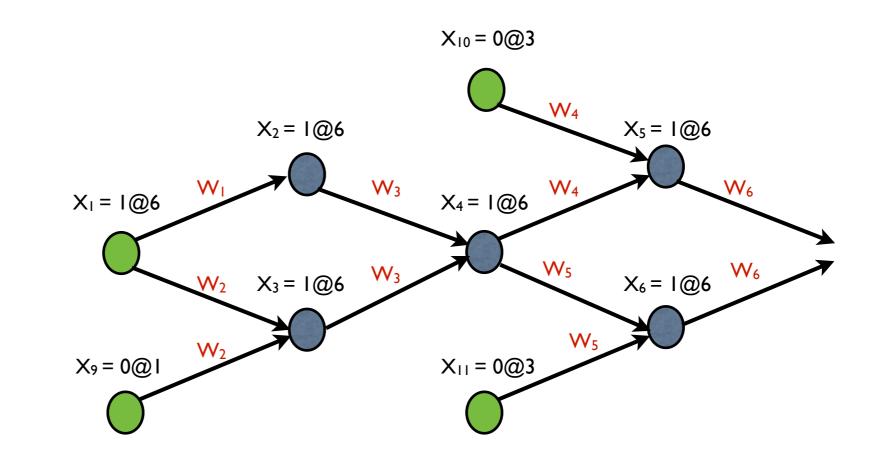
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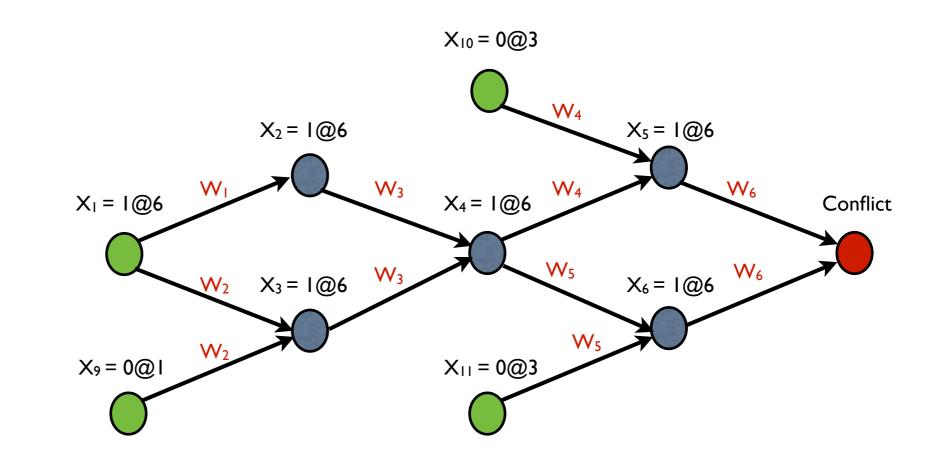
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Current Assignment Trail:  $\{X_9 = 0@1, X_{10} = 0@3, X_{11} = 0@3, X_{12} = 1@2, X_{13} = 1@2, ...\}$ 

Current decision:  $\{X_1 = 1@6\}$ 

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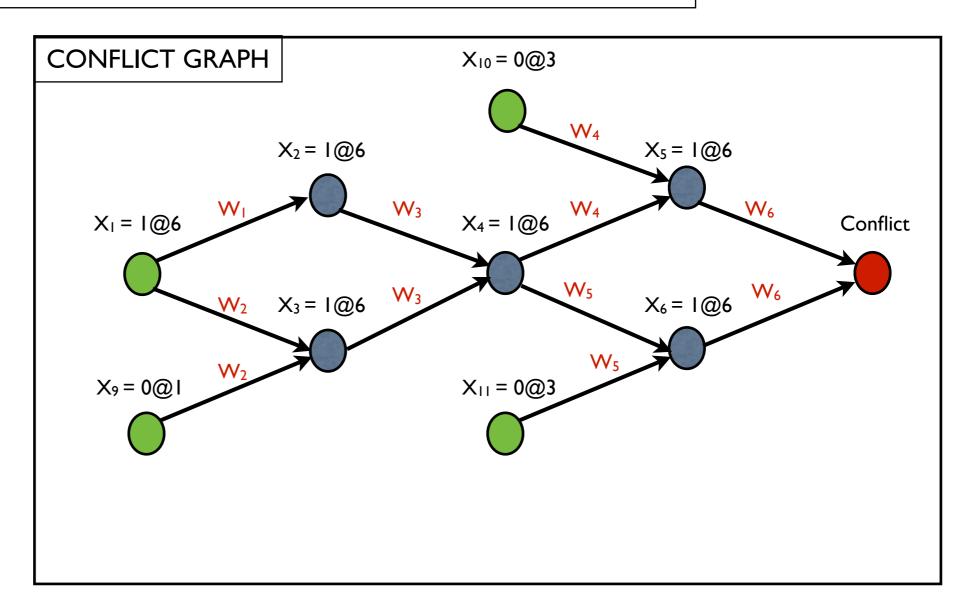
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### Modern CDCL SAT Solver Architecture Conflict Analysis/Learn() Details: Conflict Clause

Current Assignment Trail:  $\{X_9 = 0@1, X_{10} = 0@3, X_{11} = 0@3, X_{12} = 1@2, X_{13} = 1@2, ...\}$ 

Current Decision:  $\{X_1 = 1@6\}$ 

Simplest strategy is to traverse the conflict graph backwards until decision variables: conflict clause includes only decision variables ( $\neg X_1 + X_9 + X_{10} + X_{11}$ )

$$W_1 = (\neg X_1 + X_2)$$

$$W_2 = (\neg X_1 + X_3 + X_9)$$

$$W_3 = (\neg X_2 + \neg X_3 + X_4)$$

$$W_4 = (\neg X_4 + X_5 + X_{10})$$

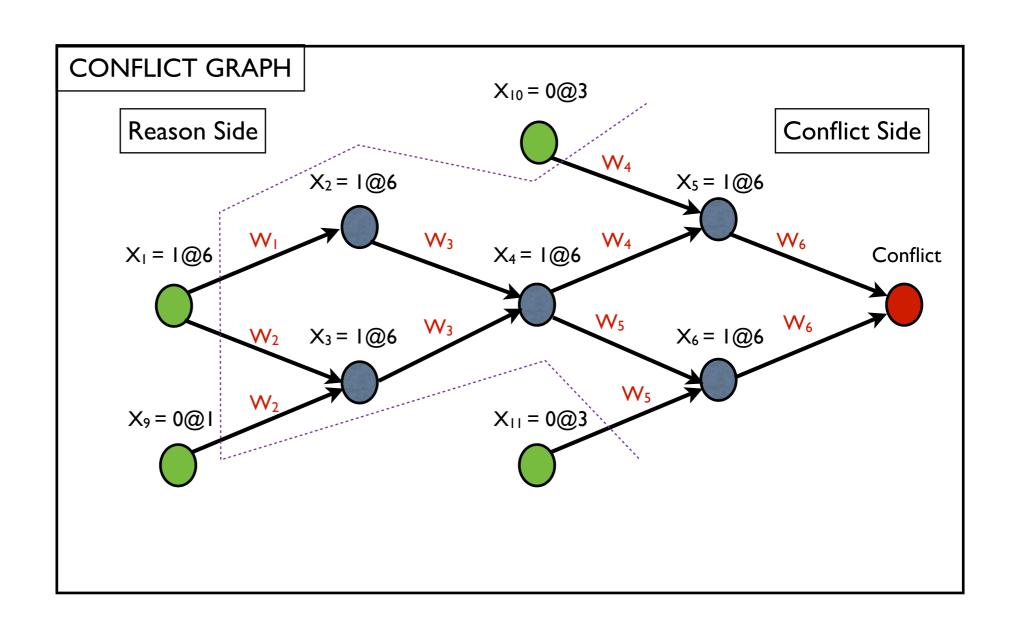
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### Modern CDCL SAT Solver Architecture Conflict Analysis/Learn() Details: Conflict Clause

Current Assignment Trail:  $\{X_9 = 0@1, X_{10} = 0@3, X_{11} = 0@3, X_{12} = 1@2, X_{13} = 1@2, ...\}$ 

Current Decision:  $\{X_1 = 1@6\}$ 

Another strategy is to use First Unique Implicant Point (UIP): Traverse graph backwards in breadth-first, expand literals of conflict, stop at first UIP

$$W_1 = (\neg X_1 + X_2)$$

$$W_2 = (\neg X_1 + X_3 + X_9)$$

$$W_3 = (\neg X_2 + \neg X_3 + X_4)$$

$$W_4 = (\neg X_4 + X_5 + X_{10})$$

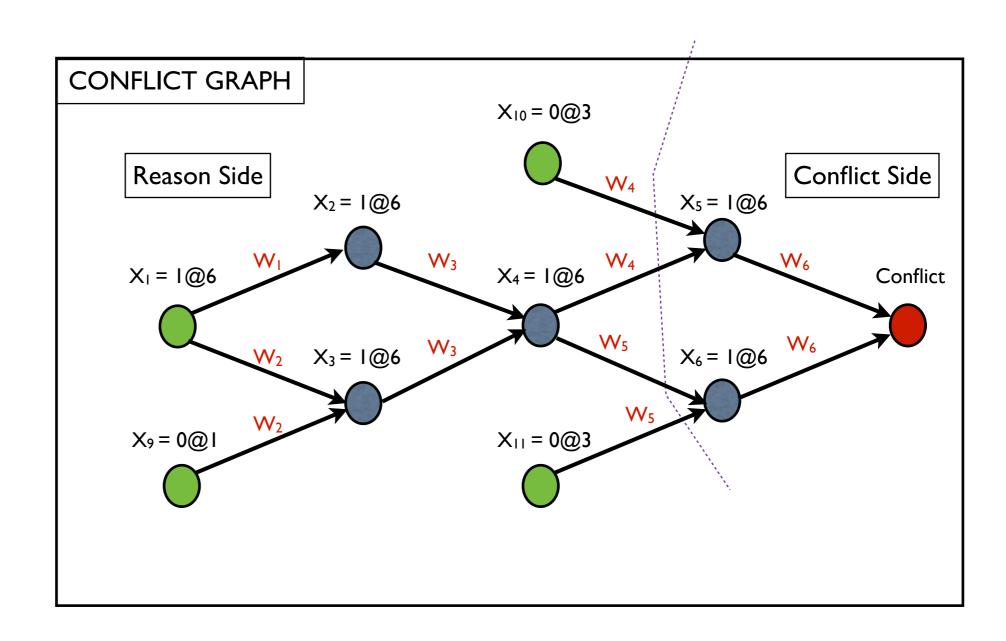
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$$W_8 = (X_1 + X_8)$$

$$W_9 = (\neg X_7 + \neg X_8 + \neg X_{13})$$



### Modern CDCL SAT Solver Architecture Conflict Analysis/Learn() Details: BackTrack

Current Assignment Trail:  $\{X_9 = 0@1, X_{10} = 0@3, X_{11} = 0@3, X_{12} = 1@2, X_{13} = 1@2, ...\}$ 

Current decision:  $\{X_1 = 1@6\}$ 

Strategy: Closest decision level (DL)  $\leq$  current DL for which conflict clause is unit. Undo  $\{X_1 = 1@6\}$ 

$$W_1 = (\neg X_1 + X_2)$$

$$W_2 = (\neg X_1 + X_3 + X_9)$$

$$W_3 = (\neg X_2 + \neg X_3 + X_4)$$

$$W_4 = (\neg X_4 + X_5 + X_{10})$$

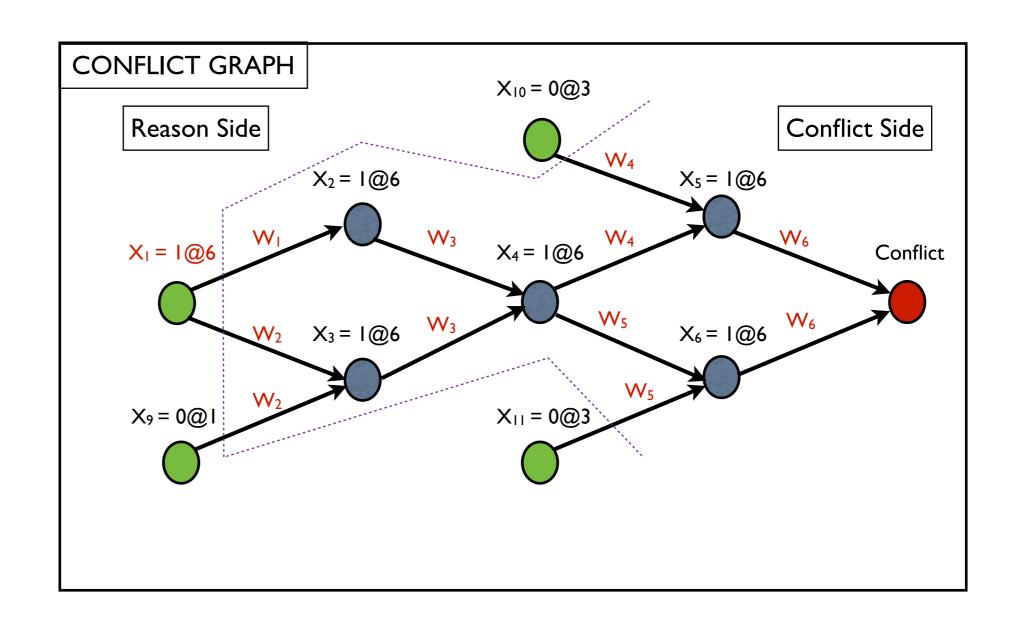
$$W_5 = (\neg X_4 + X_6 + X_{11})$$

$$W_6 = (\neg X_5 + \neg X_6)$$

$$W_7 = (X_1 + X_7 + \neg X_{12})$$

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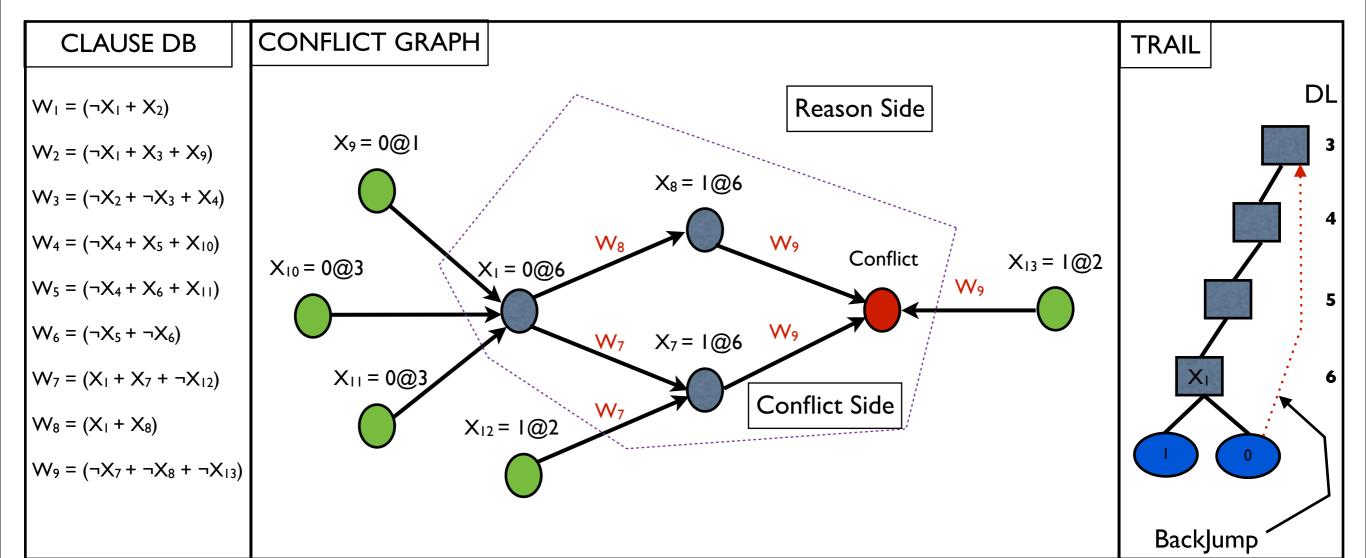


# Modern CDCL SAT Solver Architecture Conflict Analysis/Learn() Details: BackJump

 $\neg X_1$  was implied literal, leading to another conflict described below

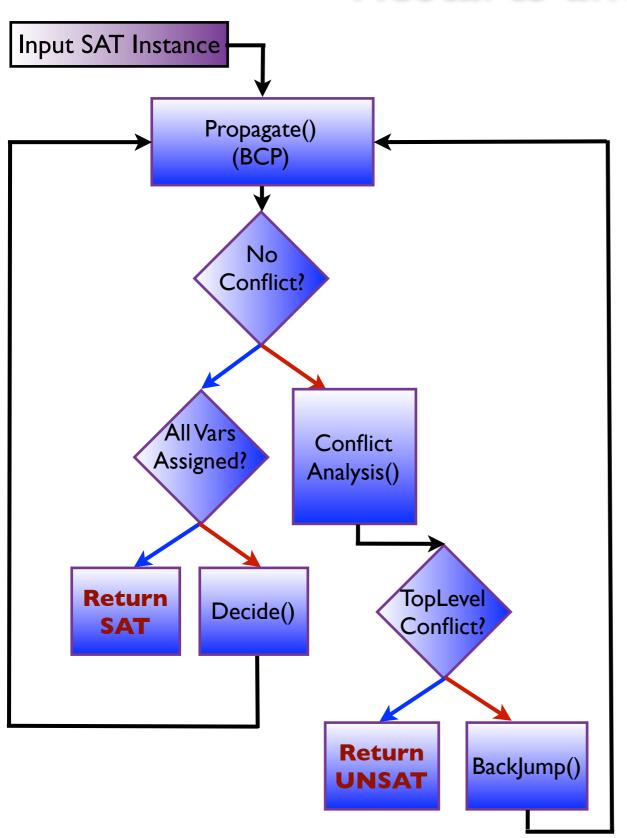
Conflict clause:  $(X_9 + X_{10} + X_{11} + \neg X_{12} + \neg X_{13})$ 

BackJump strategy: Closest decision level (DL)  $\leq$  current DL for which conflict clause is unit. Undo  $\{X_{10} = 0@3\}$ 



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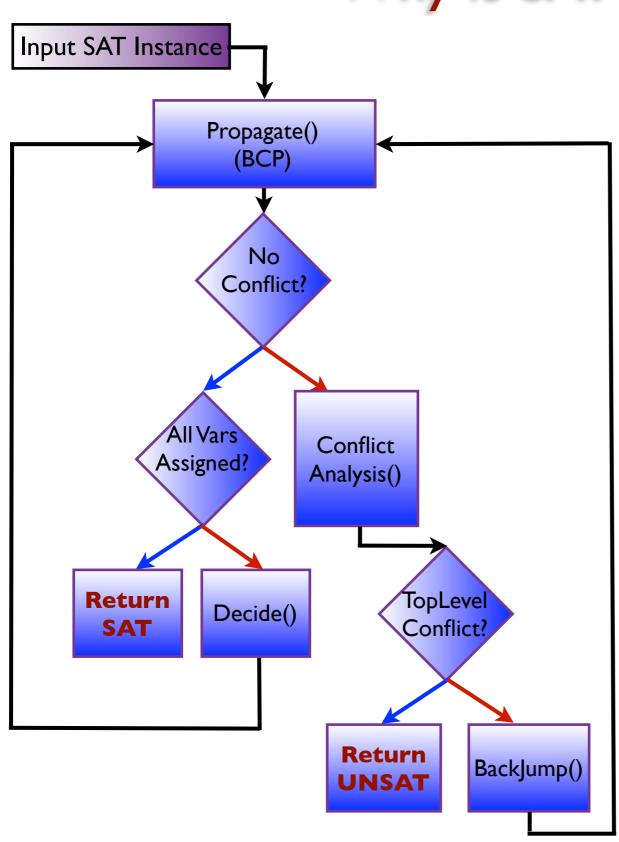
### Modern CDCL SAT Solver Architecture Restarts and Forget



#### Restarts

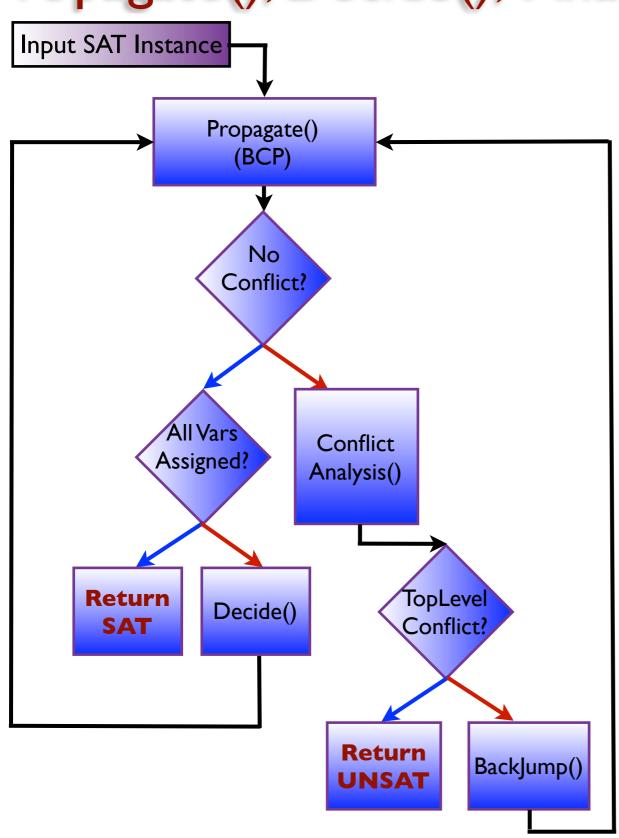
- Clear the Trail and start again
- Start searching with a different variable order
- Only Conflict Clause (CC) database is retained
- Forget: throw away less active learnt conflict clauses routinely
  - Routinely throw away very large CC
  - Logically CC are implied
  - Hence no loss in soundness/completeness
  - Time Savings: smaller DB means less work in propagation
  - Space savings

### Modern CDCL SAT Solver Architecture Why is SAT efficient?



- VSIDS branching heuristic and propagate (BCP)
- Conflict-Driven Clause-Learning (CDCL)
- Forget conflict clauses if DB goes too big
- BackJump
- Restarts
- All the above elements are needed for efficiency
- Deeper understanding lacking
- No predictive theory

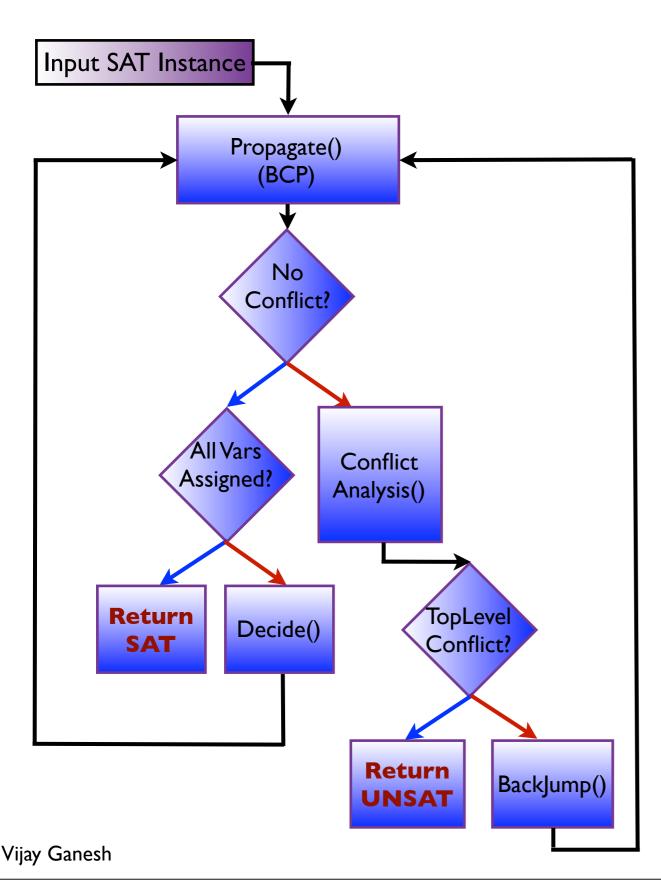
# Modern CDCL SAT Solver Architecture Propagate(), Decide(), Analyze/Learn(), BackJump()



- Conflict-Driven Clause-Learning (CDCL) (Marques-Silva & Sakallah 1996)
- Decide/branch and propagate (BCP)
   (Malik et al. 2001, Zabih & McAllester 1988)
- BackJump (McAllester 1980, Marques-Silva & Sakallah 1999)
- Restarts (Selman & Gomes 2001)
- Follows MiniSAT (Een & Sorensson 2003)

Vijay Ganesh

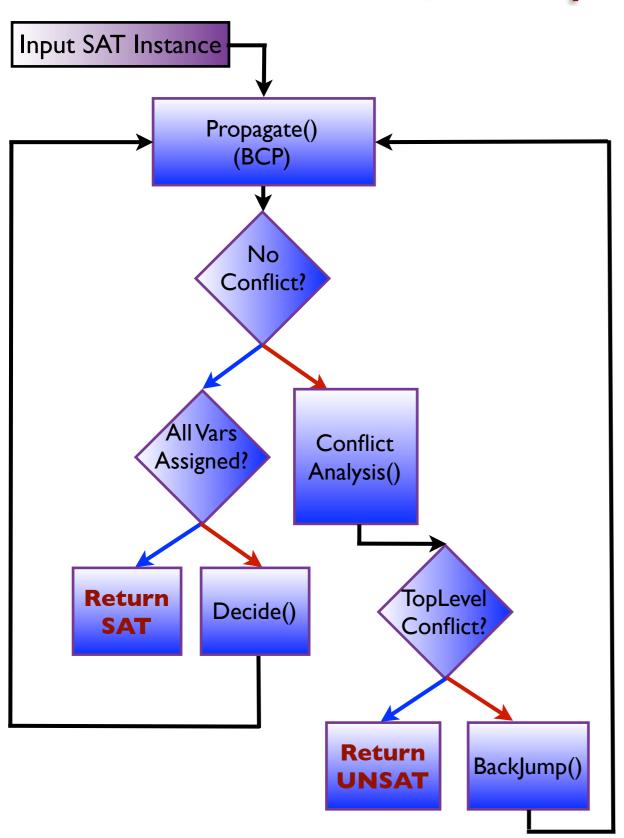
### Modern CDCL SAT Solver Architecture Soundness, Completeness & Termination



Soundness: A solver is said to be sound, if, for any input formula F, the solver terminates and produces a solution, then F is indeed SAT

Proof: (Easy) SAT is returned only when all vars have been assigned a value (True, False) by Decide or BCP, and solver checks the solution.

### Modern CDCL SAT Solver Architecture Soundness, Completeness & Termination

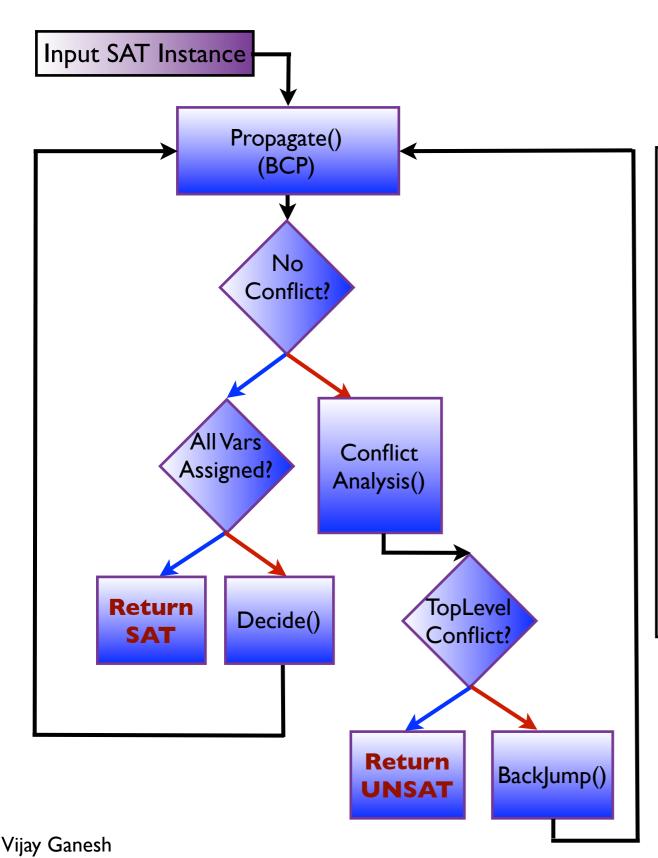


Completeness: A solver is said to be complete, if, for any input formula F that is SAT, the solver terminates and produces a solution (i.e., solver does not miss solutions)

Proof: (Harder)

- Backtracking + BCP + decide is complete (easy)
- Conflict clause is implied by input formula (easy)
- Only need to see backjumping does not skip assignments
  - Observe backjumping occurs only when conflict clause (CC) vars < decision level (DL) of conflicting var
  - Backjumping to max(DL of vars in CC)
  - Decision tree rooted at max(DL of vars in CC)+1 is guaranteed to not satisfy CC
  - Hence, backjumping will not skip assignments

### Modern CDCL SAT Solver Architecture Soundness, Completeness & Termination



Termination: Some measure decreases every iteration

#### **Proof Sketch:**

- Loop guarantees either conflict clause (CC) added
   OR assign extended
- CC added. What stops CC addition looping forever?
  - Recall that CC is remembered
  - No CC duplication possible
  - CC blocks UNSAT assign exploration in decision tree. No duplicate UNSAT assign exploration possible
  - Size of decision tree explored decreases for each CC add

### Modern CDCL SAT Solver Architecture References & Important SAT Solvers

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- 2. Marques-Silva, J.P. and K.A. Sakallah. GRASP: A Search Algorithm for Propositional Satisfiability. Proceedings of ICCAD, 1996.
- 3. M. Moskewicz, C. Madigan, Y. Zhao, L. Zhang, and S. Malik. CHAFF: Engineering an efficient SAT solver. Proceedings of the Design Automation Conference (DAC), 2001, 530-535.
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- 6. M. Davis, G. Logemann, and D. Loveland. A machine program for theorem proving. Communications of the ACM. 1962.
- 7. zChaff SAT Solver by Lintao Zhang 2002.
- 8. GRASP SAT Solver by Joao Marques-Silva and Karem Sakallah 1999.
- 9. MiniSAT Solver by Niklas Een and Niklas Sorenson 2005 present
- 10. SAT Live: <a href="http://www.satlive.org/">http://www.satlive.org/</a>
- 11. SAT Competition: <a href="http://www.satcompetition.org/">http://www.satcompetition.org/</a>
- 12. SAT/SMT summer school: <a href="http://people.csail.mit.edu/vganesh/summerschool/">http://people.csail.mit.edu/vganesh/summerschool/</a>

Vijay Ganesh

# Modern CDCL SAT Solver Architecture Important Ideas and Conclusions

- I. SAT solvers are crucial for software engineering
- 2. Huge impact in formal methods, program analysis and testing
- 3. Key ideas that make SAT efficient
  - I. Conflict-driven clause learning
  - 2. VSIDS (or similar) variable selection heuristics
  - 3. Backjumping
  - 4. Restarts
- 4. Techniques I didn't discuss
  - I. Survey propagation (belief propagation) by Selman & Gomes
  - 2. Works well for randomized SAT, not yet for industrial instances
  - 3. Physics-inspired
  - 4. Combining CDCL with survey propagation (?)

Vijay Ganesh