

Lecture 4: Modern Techniques in SAT Solving

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Recap: Iterative DPLL

```
dpll(\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 decision level = 0: return UNSAT
         backtrack()
         set x = F
return SAT
```



Chronological Backtracking

- DPLL uses **chronological backtracking**: when we find a conflict, backtrack to the previous decision level
- **Issue:** might reach conflicts (contradictions) caused by the same underlying reason over and over again



Chronological Backtracking

 $(1 \lor \overline{2})$ $(\overline{1} \lor 3 \lor 4)$ $(\overline{1} \lor \overline{3} \lor 4)$ $(\overline{1} \lor 3 \lor \overline{4})$ $(\overline{1} \lor 3 \lor \overline{4})$



Chronological Backtracking









Backjumping

- Not every decision actually contributes to a conflict
- Idea: upon conflict, instead of backtracking one level to the last decision, **backjump** to an *important* decision
 - o i.e., a decision that contributed to the conflict
- But how do we know what is an important decision?



Implication Graphs

- An **implication graph** *G* is a DAG whose vertices are literal assignments at a particular decision level
 - Ex: $\overline{x}@3$ represents setting x to False at level 3
 - Assignments can be decisions or due to unit propagation/backtracking
- Can also contain special vertex \bot representing a conflict
- There is an edge $x@i \rightarrow y@j$ if the assignment x@i directly implied the assignment y@j
 - i.e., y@j was set by unit propagation from a clause containing \overline{x}



























Conflicts



- A conflict set of assignments (collectively) imply a conflict
- A conflict cut in an implication graph is a bipartition of the vertices V = R U C such that:
 - *Reason side R* contains all decisions (source nodes)
 - *Conflict side C* contains the conflict node (a sink)
 - No edges cross $C \to R$, only $R \to C$
- The set of vertices with an outgoing edge crossing a given conflict cut forms a conflict set



Clause Learning



- **Observation:** Given a conflict set {*x*₁, *x*₂, ..., *x*_k}, we know at least one literal in the set must be False
- Can derive the **conflict clause** $(\overline{x_1} \lor \overline{x_2} \lor \cdots \lor \overline{x_k})$
- **Conflict-driven clause learning (CDCL):** add conflict clauses to the original CNF we're solving
 - Introduced by GRASP (1996); revolutionized SAT solving
 - Many solvers have aggressive deletion policy for long, "inactive,"
 "unhelpful" learned clauses avoid explosion in CNF size

Asserting Clauses

- Many conflict cuts how do we decide which to choose to build a conflict clause?
- **Goal:** after backjumping, be able to apply new knowledge from learned clause right away
 - Want learned clause to become a unit clause right after backjumping

Asserting Clauses

- A learned clause is **asserting** if it contains only one variable set on the same decision level as conflict
 - Is it possible for any conflict clause to contain zero?
- **Observation:** iff a clause is asserting, it will become a unit clause after backtracking
- How far can we backjump and still have asserting clauses become unit clauses?
 - Backjump to *second-largest* (i.e., deepest) decision level in asserting clause (or zeroth level if asserting clause has size 1)
 - i.e., return to that decision level (don't undo the decision)
 - Called the **asserting level**

CDCL (Pseudocode)

```
\operatorname{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
```























Unique Implication Points

- Unique implication point (UIP): a node in the implication graph that all paths from the most recent decision variable to the conflict must pass through
- Intuition: at the decision level of the conflict, the UIP is a literal that, by itself, implies a contradiction



The 1-UIP Scheme

- The "first" UIP is the closest UIP to the conflict node
 - o i.e., the "rightmost"
- When we reach a conflict, cut after the first UIP
 - Generally produces shortest learned clauses









1-UIP Backjump $c_1: \overline{2} \vee \overline{3} \vee \overline{4}$ **Backjump!** c_2 : $\overline{3} \vee \overline{5} \vee \overline{6}$ $c_3: 4 \vee 6 \vee 7$ c_4 : $\overline{7} \vee \overline{8}$ c_5 : $1 \vee \overline{7} \vee \overline{9}$ $c_6: 1 \vee 8 \vee 9$ *c*: $1 \vee \overline{7}$









Restarts

- Problem: if we make bad early guesses, can get stuck in fruitless areas of search tree
- Solution: periodically **restart** the search throw away the current partial assignment
 - Modern solvers favor aggressive restart policy
 - MiniSAT, PicoSAT: every ~100 conflicts
 - Key idea: CDCL is deterministic, so why won't we end up back where we were?
 - Learned clauses remain in formula after restart



Incremental SAT Solving

• CDCL solvers give us a new method in our toolkit!

add_clause(C): add clause C to the formula

- New clauses can only rule out previously satisfying assignments
- Can re-solve CNF with new clauses added
- Key: keep learned clauses generated during last call to solve()
- Simple use case: generating all satisfying assignments



Introducing: PennSAT

- HW2: PennSAT (due on Tue 2/21 by 4pm)
- Features:
 - DPLL-based
 - Iterative
 - Maintains propagation queue
 - No Two-Watched Literals
 - Static most-frequent decision heuristic
- This assignment is tricky **start early!**
 - Requires solid understanding



Testing a SAT Solver

- SAT solvers have tons of complicated logic... how to check for soundness bugs?
 - Hard and tedious to figure out all cases to unit test
- **Random testing:** generate random CNF formulas to test against reference solver
- If reference solver is not available, can at least check that satisfying assignments are valid



Debugging a SAT Solver

- Once we've found a bug, how do we find the mistake in the code?
- **Print debugging:** stick a bunch of print statements in relevant places and look at the console
- Easy, but not as effective for complex systems
 Easy to forget to print something, or print in wrong place



Debugging a SAT Solver







• **Debugger:** allows us to stop program mid-execution, run code line-by-line, inspect values of local variables

45 🗸	<pre>definit(self, n: int, cnf: CNF, activity_hew</pre>
46	# The number of variables
47	self.n = n
48	# The CNF as a list of clauses
🔒 Breakpoir	t self.cnf = preprocess(cnf)
50	# A stack of partial truth assignments: list
51	<pre>self.assignment_stack = [[None] * (n+1)]</pre>

• **Breakpoint:** STOP at this line of code



• After breakpoints set: Run > Start Debugging (F5)





• Control flow:



- Continue (F5): run until next breakpoint hit
 - Step Over (F10): run just one more line of code
- C
- Restart (Ctrl+Shift+F5): start over from beginning
- Stop
- Stop (Shift+F5): quit the debugger



Step Into (F11): enter code of first function called on the current line and resume debugging there



- Step Out (Shift+F11): run until the current function returns; resume debugging from parent function
- Can click to view different levels of the call stack
 - Useful for inspecting values of local vars in different scopes

\sim CALL STACK	PAUSED ON STEP	45	<pre>definit(self, n: int, cnf:</pre>
preprocess	PennSAT.py 19:1	46	<pre># The number of variables</pre>
init	PennSAT.py 49:1	47	self.n = n
<module></module>	PennSAT ny 196.1	48	# The CNF as a list of clau
	rennova.py 150.1	• 49	<pre>self.cnf = preprocess(cnf)</pre>



 \mathbf{v}

45	<pre>definit(self, n: int, cnf;</pre>
46	# The number of variables
47	self.n = n
48	# The CNF as a list of clau
b 49	<pre>self.cnf = preprocess(cnf)</pre>

	17	<pre>def preprocess(cnf: CNF) -> CNF:</pre>
	18	"""Remove duplicate literals
<pre>19 cnf = [list(set(clause))</pre>		
	20	cnf.sort()
	21	return list(clause for clause
	າງ	



45	<pre>definit(self, n: int, cnf</pre>
46	# The number of variables
47	self.n = n
48	# The CNF as a list of cla
49	<pre>self.cnf = preprocess(cnf)</pre>
50	# A stack of partial truth
51	<pre>self.assignment_stack = [[]</pre>

References

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