CSE4051: Program Verification Applications of SAT

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SAT solvers can be used in various applications

- Hardware and software verification
- Automated testing of circuits
- Package management
- Artificial intelligence (e.g., planning, scheduling)
- Cryptography
- Computational Biology
- ...

- In this lecture, we will try to solve various satisfiability problems using a SAT solver called Z3.
- Z3 is a high-performance theorem prover developed by Microsoft Research.
- We will use Z3Py, the Python interface for Z3, to write and solve logical formulas.

Using Z3Py

- Install Z3Py using pip: pip install z3-solver
- Import Z3Py in your Python script: from z3 import *
- Define Boolean variables:

• Create logical formulas using Z3Py:

$$f1 = And(Not(a), Not(b))$$

 $f2 = Or(a, b)$

Solve the satisfiability problem:

$$solve(Not(f1 == f2))$$

• The `solve` function will return whether the formula is satisfiable or not, and if it is, it will provide an interpretation that satisfies the formula.

Verifying Correctness of Optimizations

Optimization of if-then-else chains

optimized C code original C code if(!a && !b) h(); if(a) f(); else if(!a) g(); else if(b) g(); else f(); else h(); if(!a) { if(a) f(); if(!b) h(); \Rightarrow else { if(!b) h(); else g(); } else f(); else g(); }

Verifying Correctness of Optimizations

• Represent procedures as Boolean variables

$$egin{array}{ll} \emph{original} := & \emph{optimized} := \\ & \mathbf{if} \ \lnot a \land \lnot b \ \mathbf{then} \ h & \mathbf{if} \ a \ \mathbf{then} \ f & \mathbf{else} \ \mathbf{if} \ \lnot a \ \mathbf{then} \ g & \mathbf{else} \ f & \mathbf{else} \ h & \mathbf{else} \ h & \mathbf{f} & \mathbf{$$

Compile if-then-else chains into Boolean formula

compile(if x then y else z)
$$\equiv (x \land y) \lor (\neg x \land z)$$

Check equivalence of Boolean formula

$$| compile(original) \Leftrightarrow compile(optimized) |$$

Verifying Correctness of Optimizations

original
$$\equiv$$
 if $\neg a \wedge \neg b$ then h else if $\neg a$ then g else h

$$\equiv (\neg a \wedge \neg b) \wedge h \vee \neg (\neg a \wedge \neg b) \wedge \text{if } \neg a \text{ then } g \text{ else } f$$

$$\equiv (\neg a \wedge \neg b) \wedge h \vee \neg (\neg a \wedge \neg b) \wedge (\neg a \wedge g \vee a \wedge f)$$

$$(\neg a \land \neg b) \land h \lor \neg (\neg a \land \neg b) \land (\neg a \land g \lor a \land f) \quad \Leftrightarrow \quad a \land f \lor \neg a \land (b \land g \lor \neg b \land h)$$

Suppose now the optimized version is

if !a then h else if b then g else f

• Is it still equivalent to the original one?

Or (And(Not(a), h), And(a, Or(And(b, g), And(Not(b), f)))

Seat Assignment

- Consider three persons 1, 2, and 3 who need to be seated in a row. There are three constraints:
 - I does not want to sit next to 3
 - I does not want to sit in the leftmost chair
 - 2 does not want to sit to the right of 3
- We would like to check if there is a seat assignment for the three persons that satisfies the above constraints.

From https://prl.korea.ac.kr/courses/aaa528/2025/slides/lec3.pdf

Encoding of Seat Assignment

• Let X_{ij} be boolean variables such that

$$X_{ij} \iff \text{person } i \text{ seats in chair } j$$

Constraints

Every person is seated:
$$\bigwedge_{i=1}^{3} \bigvee_{j=1}^{3} X_{ij}$$

Every seat is occupied: $\bigwedge_{j=1}^{3} \bigvee_{i=1}^{3} X_{ij}$

One person per seat:
$$\bigwedge (X_{i,j} \Longrightarrow \bigwedge \neg X_{i,k})$$

$$i,j \in \{1,2,3\}$$

$$k,j \in \{1,2,3\}, k \neq j$$

Encoding of Seat Assignment

Person I does not want to sit next to person 3:

$$(X_{00} \Longrightarrow \neg X_{21}) \land (X_{01} \Longrightarrow (\neg X_{20} \land \neg X_{22})) \land (X_{02} \Longrightarrow \neg X_{21})$$

 \circ Person I does not want to sit in the leftmost chair: $\neg X_{00}$

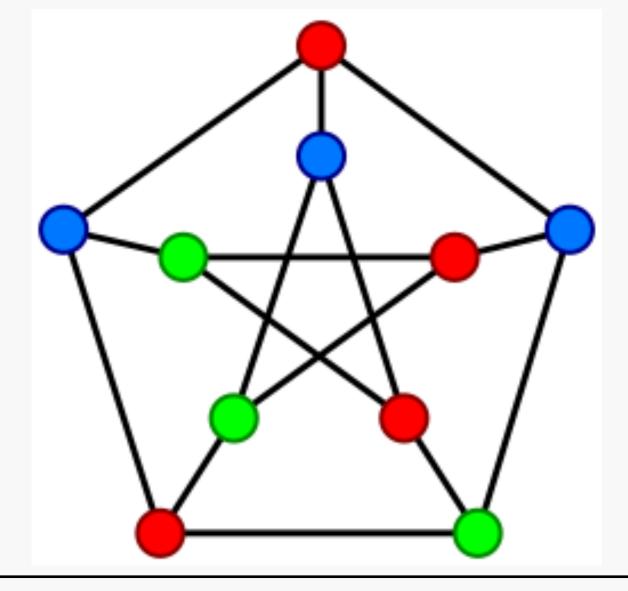
Person 2 does not want to sit to the right of person 3:

$$(X_{20} \Longrightarrow \neg X_{11}) \land (X_{21} \Longrightarrow \neg X_{12})$$

• Remove the constraint "Person I does not want to sit in the leftmost chair" and get a seat assignment.

Or (And(Not(a), h), And(a, Or(And(b, g), And(Not(b), f))))

- A graph is k-colorable if there is an assignment of k colors to its vertices such that no two adjacent vertices have the same color.
- Deciding if such a coloring exists is a classic NP-complete problem with many practical applications, such as register allocation in compilers.
- For example, a coloring with 3 colors of a graph:

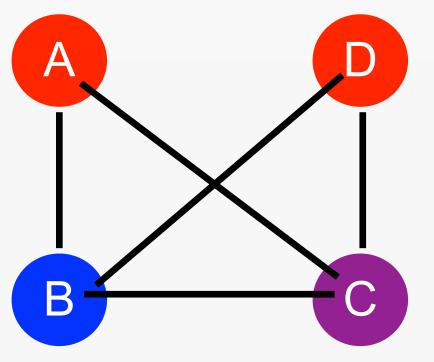


- A finite graph $G = \langle V, E \rangle$ where $V = \{v_1, ..., v_n\}$ is a set of vertices and $E = \{(v_{i1}, w_{i1}), ..., (v_{im}, w_{im})\}$ is a set of edges. Given a set of k colors in $C = \{c_1, ..., c_k\}$, the k-coloring problem for G is to assign a color $c \in C$ to each vertex $v \in V$ s.t. for every edge $\langle v, w \rangle \in E$, color $(v) \neq \text{color}(w)$.
- Introduce Boolean variables x_{ij} such that $x_{ij} \iff v_i$ is assigned color c_j
- Conditions
 - Every vertex is assigned at least one color.
 - Every vertex is assigned not more than one color.
 - Neighbors are not assigned the same color

```
1 from z3 import *
 3 # Define the graph
 4 \text{ graph} = {
      'A': ['B', 'C'],
     'B': ['A', 'C', 'D'],
     'C': ['A', 'B', 'D'],
 8 9 }
      'D': ['B', 'C']
10
11 nodes = list(graph.keys())
12 k = 3 # number of colors
13
14 # Step 1: Create Boolean variables: color_vars[node][color]
15 color_vars = {
      node: [Bool(f"{node}_{c}") for c in range(k)]
16
17
      for node in nodes
18 }
20 solver = Solver()
```

```
21
22 # Step 2: Each node must have exactly one color
23 for node in nodes:
      # At least one color
25
      solver.add(0r(color_vars[node]))
26
27
      # At most one color
28
      for c1 in range(k):
           for c2 in range(c1 + 1, k):
29
               solver.add(Not(And(color_vars[node][c1], color_vars[node][c2])))
30
31
32 # Step 3: Adjacent nodes must not share the same color
33 for node in graph:
       for neighbor in graph[node]:
34
           if node < neighbor: # avoid duplicate constraints</pre>
35
36
               for c in range(k):
37
                   solver.add(0r(Not(color_vars[node][c]), Not(color_vars[neighbor][c])))
38
```

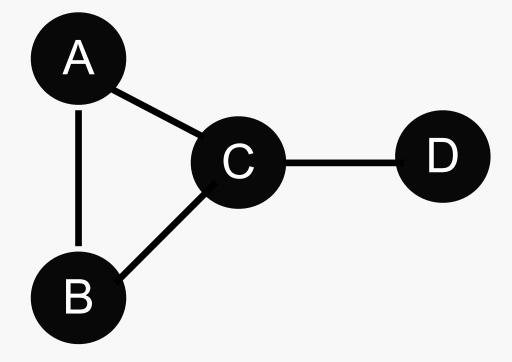
```
39 # Step 4: Solve and display
40 if solver.check() == sat:
41
      model = solver.model()
42
     print("Coloring found:")
     for node in nodes:
43
44
          for c in range(k):
              if model.evaluate(color_vars[node][c]):
45
                  print(f" {node}: Color {c}")
46
47 else:
      print("No valid coloring found.")
```



Coloring found:

A: Color 1
B: Color 2
C: Color 0
D: Color 1

• Consider the graph on the right.



Get all possible 3-colorings of the graph.

for node in nodes:
 for c in range(k):
 lit = color_vars[node][c]
 if m.evaluate(lit):
 block.append(Not(lit)
 else:
 block.append(lit)

Package Management

- Install problem: determining whether a new set of packages can be installed in a system
- Many packages depend on other packages to provide some functionality.
- Each distribution contains a meta-data file containing the name, version, etc.
- More importantly, it contains depends and conflicts clauses that stipulate which other packages should be on the system.

Package Management

```
Package: apache
Architecture: i386
Version: 1.3.34-2
Provides: httpd-cgi, httpd
Depends: libc6(>=2.3.5-1),
  libdb4.3(>=4.3.28-1),
  debconf(>=0.5) | debconf-2.0,
  apache-common(>=1.3.34-2),
  perl(>=5.8.4-2)
Conflicts: apache-modules,
  jserv(<=1.1-3)
  libapache-mod-perl
Description: HTTP server.</pre>
```



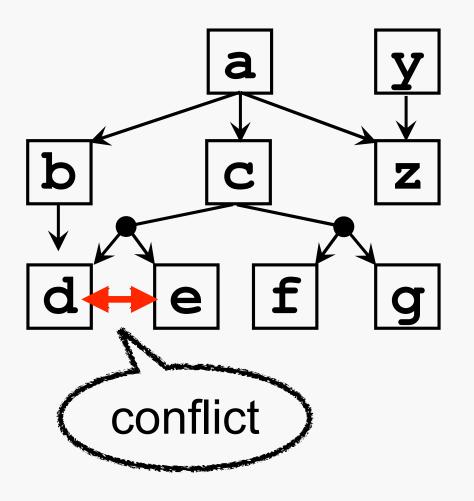


Figure 2: Distribution Graph

$x_a \iff$ package a is installed

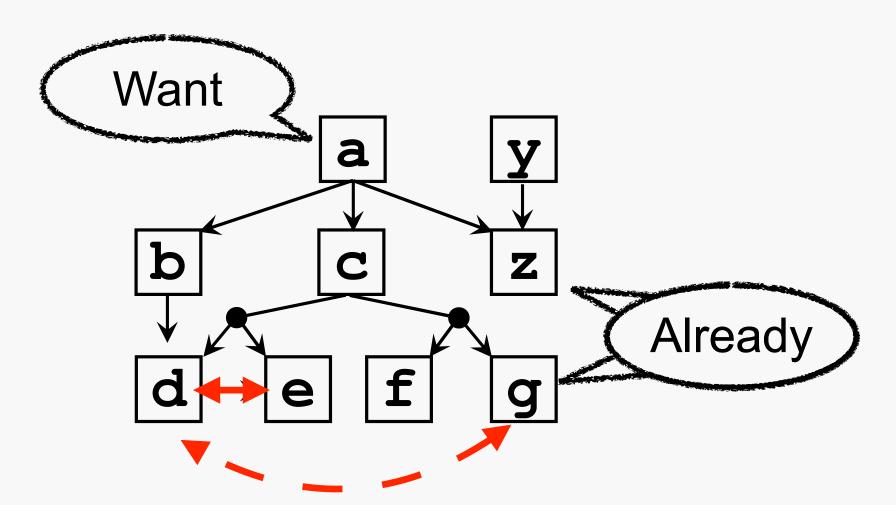
Distribution Rules	Constraints
Package: a	
Depends: b,	$(\neg x_{\mathtt{a}} \lor x_{\mathtt{b}})$
C ,	$(\neg x_{a} \lor x_{c})$
Z	$(\neg x_{\mathtt{a}} \lor x_{\mathtt{z}})$
Package: b Depends: d	$(\neg x_{b} \lor x_{d})$
Package: c Depends: d e, f g	$(\neg x_{c} \lor x_{d} \lor x_{e})$ $(\neg x_{c} \lor x_{f} \lor x_{g})$
Package: d Conflicts: e	$(\neg x_{d} \lor \neg x_{e})$

Figure 3: Fragment of Distribution Metadata and Corresponding Constraints

The formula will be the constraints in Figure 3 along with packages to be installed and already installed

Package Management

• Installation in the presence of conflicts: to install "a" while minimizing the number of removed components, what can we do?



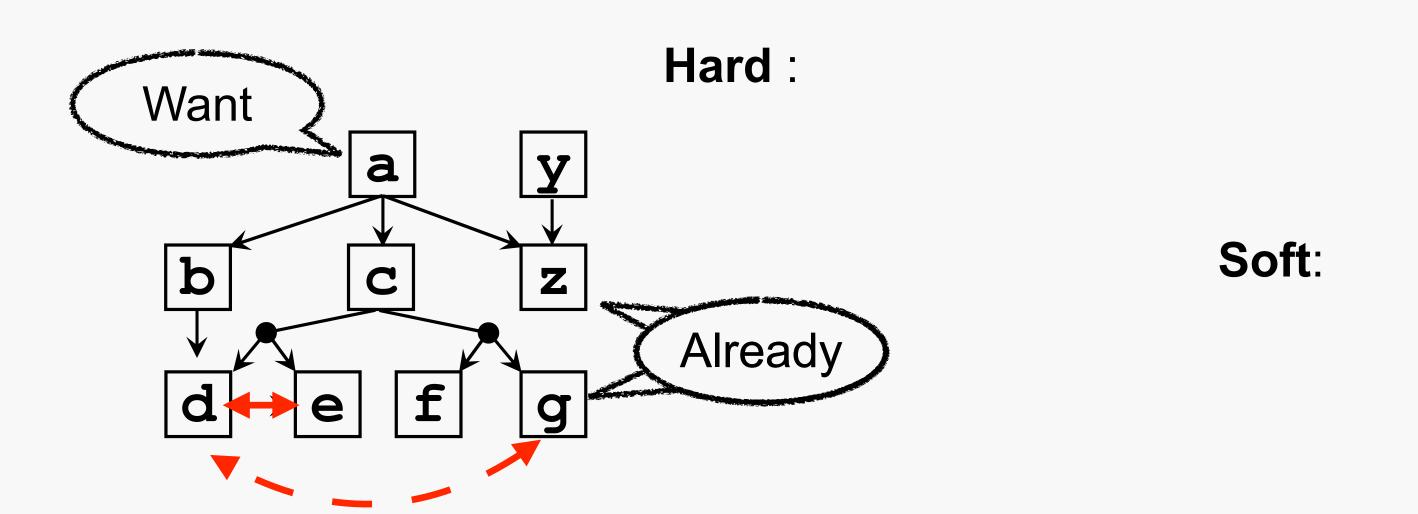
MaxSAT

- Given a formula F in CNF, find assignment maximizing the number of satisfied clauses of F
 - o If F is satisfiable, the solution is simply the number of clauses in F
 - If F is unsatisfiable, we want to find a maximum subset of F's clauses whose conjunction is satisfiable
 - For $(a \lor b) \land \neg a \land \neg b$, a solution is $\{a \mapsto \bot, b \mapsto \bot\}$

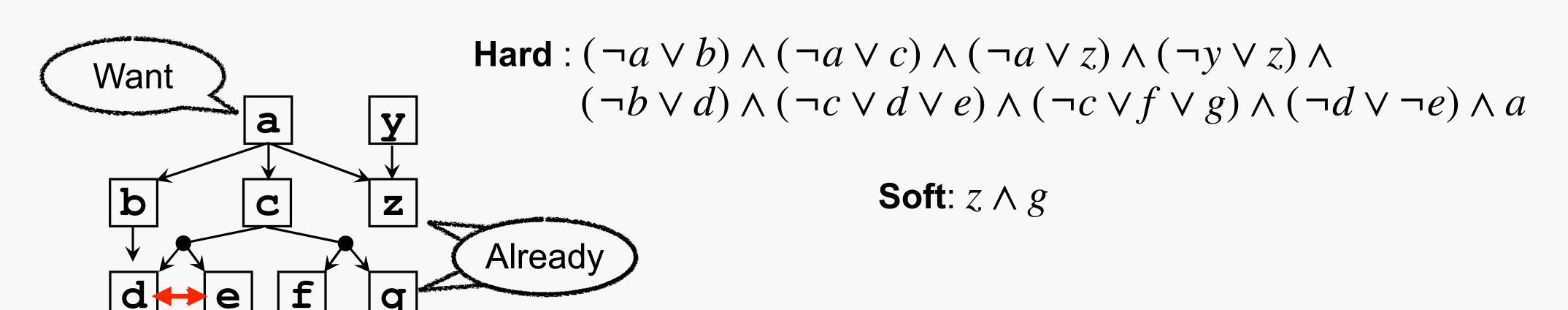
Partial MaxSAT

- The goal is the same as MaxSAT except that we have
 - Hard constraints: clauses that must be satisfied
 - Soft constraints: clauses that do not have to be satisfied but we want to satisfy as many as possible
- Goal: Given a formula in CNF marked as hard or soft, find an assignment that satisfies all hard constraints and maximizes the number of satisfied soft constraints

- Installation in the presence of conflicts: to install "a" while minimizing the number of removed components, what can we do?
 - => we can encode the problem as a partial MaxSAT problem and solve it.



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Partial Weighted MaxSAT

- Soft clauses have weights indicating their importance.
- Goal: Find assignment maximizing the sum of weights of satisfied soft clauses
- Partial MaxSAT is an instance of partial weighted MaxSAT where all clauses have equal weight.

• To install "a" minimizing the total size of removed components, assuming z and g are 5MB and 2MB each

