SAT-Solving: From Davis-Putnam to Zchaff and Beyond Day 1: SAT Basics





Automated Reasoning: Motivations

- As a curiosity of mathematicians and inventers
 - Demonstrator, Charles Stanhope, 1777
 - Logic Machine, William Stanley Jevons, 1869
- Artificial Intelligence and foundation of mathematics
 - Mechanical theorem proving
 - Reasoning on knowledge base
- Electronic Design Automation
 - ATPG
 - Logic synthesis
- Verification of digital systems
 - Equivalence checking
 - Model checking
 - Safety of programs, concurrent processes





How to Perform Automatic Reasoning?

- Modeling: Abstract the problem into logic
 - Boolean propositional logic
 - Temporal logic
 - Set theory
 - First order logic
- Proof: Use automatic decision procedures to determine the correctness (*validity*) of the resulting logic
 - SAT Solvers and BDDs
 - Model Checker
 - Theorem Provers





Propositional Logic

- Variable Domain: True/False or 1/0
- Logic operations: and $\land \cdot$, or $\lor +$, not \neg '
 - It's also easy to express **Imply** \rightarrow , equivalence \leftrightarrow
- If a and b are Boolean, then these are propositional formulas:
 - $\mathbf{a} \cdot \mathbf{b} + \mathbf{a}' \cdot \mathbf{c}$
 - $1 \cdot a = 0$
 - 1+a = 1
- These are not propositional logic:
 - 3 + x = x + 3;
- -- Integer domain
 - ∀a ∃b (a+b)(a'+b')
 -- Quantifiers
 - If a = b then f(a)=f(b) -- Uninterpreted function
- It is the basis of all other logics.









What is SAT?

- Boolean Satisfiability (SAT).
- Operates on Boolean Propositional Logic
- Check if a complex logical relationship can ever be true (or satisfiable)
 - x OR y is true when x is true or y is true (satisfiable)
 - x AND (NOT x) can never be true (unsatisfiable)
- Tautology Checking
- Looks easy, but gets hard very quickly as the size of the problem increases
 - Size measured in terms of:
 - Number of variables
 - Number of operations





Why is SAT Important?

- Theoretical importance
 - It's the first NP-Complete problem discovered by Cook in 1971
- It's everywhere
 - Automatic Test Pattern Generation
 - Combinational Equivalence Checking
 - Bounded Model Checking
 - Al Planning
 - Theorem Proving
 - Software modeling and verification
 -
- We have powerful SAT solvers that can solve practical problems
 - SAT solving has been well studied for at least 40 years.
 - Recent breakthroughs make SAT solver highly efficient
 - Can handle over a million variables and operations
 - Seen wide use in the industry
 - Can we do better?

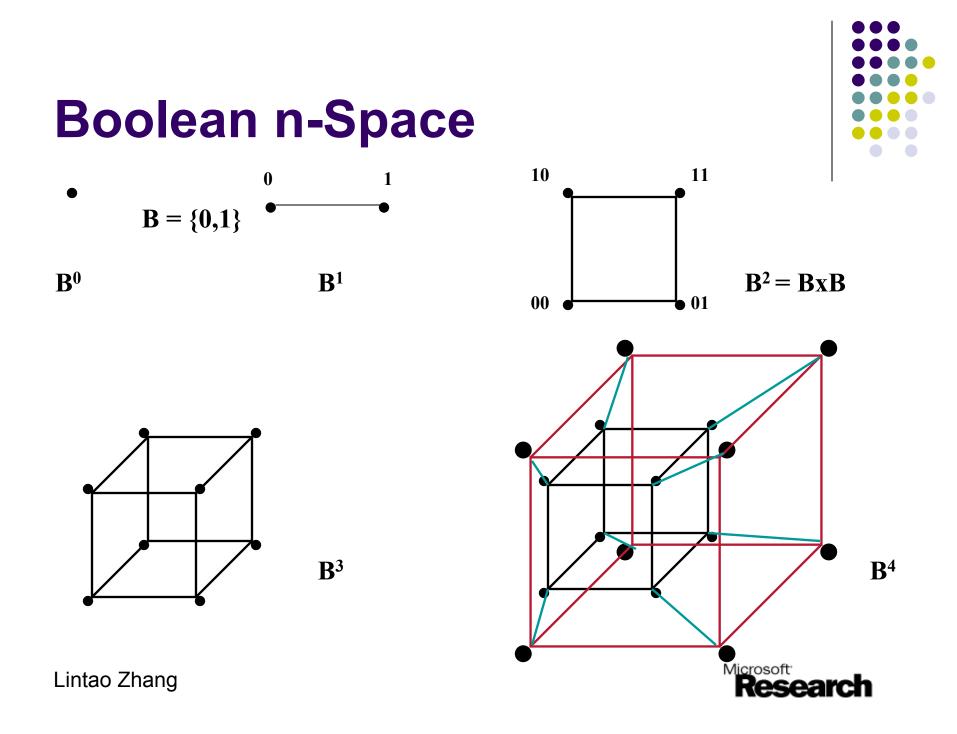


Course Schedule

- 3-day mini-course
 - Today: Basics of SAT solving
 - Tomorrow: Efficient Implementation of SAT solvers
 - Wednesday: Recent Developments in SAT research
- Emphasis on Engineering, not math or just algorithms
- Lectures in the morning, projects and discussion in the afternoon
- Main course project: Implementing an SAT solver
 - Require some knowledge of C/C++ and STL



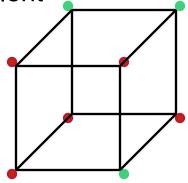




Boolean Functions

 $f(x): B^n \rightarrow B \qquad B=\{0,1\} \qquad x=\{x_1, x_2, \dots x_n\}$

- $x_1, x_2, \dots x_n$ are variables
- Each vertex of Bⁿ is mapped to either 0 or 1
- The on-set of f is $\{x|f(x) = 1\} = f^1 = f^{-1}(1)$
- The off-set of f is $\{x|f(x) = 0\} = f^0 = f^{-1}(0)$
- If f¹ = Bⁿ, f is a tautology
- If $f^0 = B^n$, i.e. $f = \phi$, f is not satisfiable
- If f(x) = g(x) for all $x \in B^n$, then f and g are equivalent
- Also referred to as logic functions
- How many logic functions are there?



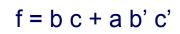


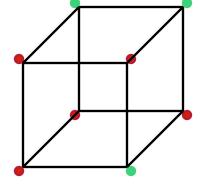


Representation of Boolean Functions

- The truth table for a function f: Bⁿ ->B is a tabular representation of its value at each of the 2ⁿ vertices of Bⁿ.
- Example:

abc	f
000	0
001	0
010	0
011	1
100	1
101	0
110	0
111	1





- Intractable for large n (but canonical).
- Canonical means that if two functions are equivalent, then their canonical representations are isomorphic.





Boolean Satisfiability

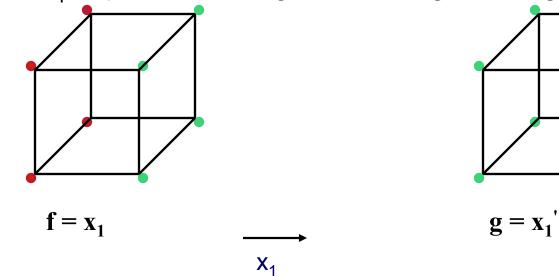
- Is there a any satisfying assignment for the function, i.e. is there at least one point in the ON-set of the function?
- How hard is this?
 - Depends on how the function is represented.
 - Boolean n-cube, truth table
 - Easy once we have the representation
 - But representation size is exponential in n ⊗
 - How about other representation?
 - Boolean Formula
 - BDD
 - Circuit





Literals

- A literal is a variable or its negation.
 - x_1, x_1' (also represented as $\neg x_1$)
- Literal x_1 represents a logic function f where $f^1 = \{x | x_1 = 1\}$
- Literal x_1' represents a logic function g where $g^1 = \{x|x_1=0\}$





Boolean Formulas



- Parenthesis (,)
- Literals x_1, x_1'
- Boolean operators + (OR), x or . (AND), NOT
- NOT (Negation) : f' = h such that $h^1 = f^0$
- AND (Conjunction): (f AND g) = h such that $h^1 = \{x | f(x) = 1 \text{ and } g(x) = 1\}$
- OR (Disjunction): (f OR g) = h such that $h^1 = \{x | f(x) = 1 \text{ or } g(x) = 1\}$
- Usually replace x with catenation
 - e.g. $x_1 \ge x_2$ with $x_1 \ge x_2$
- How many formulas can we have with n variables?
- Examples:

•
$$f = x_1 x_2' + x_1' x_2$$

= $(x_1 + x_2) (x_1' + x_2')$

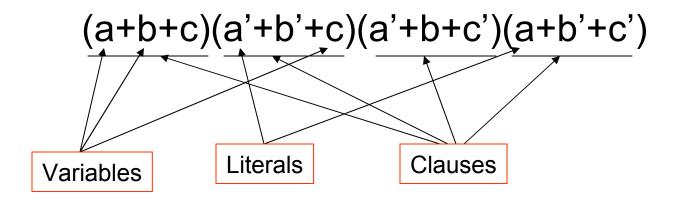
•
$$h = x_1 + x_2 x_3$$

= $(x_1' (x_2' + x_3'))'$



Boolean Satisfiability (SAT)

- Given a Boolean propositional formula, determine whether there exists a variable assignment that makes the formula evaluate to *true*.
- Formulas are often expressed in *Conjunctive Normal Form (CNF)*





Boolean Satisfiability (SAT)

- Given a Boolean propositional formula, determine whether there exists a variable assignment that makes the formula evaluate to *true*.
- Formulas are often expressed in *Conjunctive Normal Form (CNF)*

$$(a+b+c)(a'+b'+c)(a'+b+c')(a+b'+c')$$





Boolean Satisfiability (SAT)

- Given a Boolean propositional formula, determine whether there exists a variable assignment that makes the formula evaluate to *true*.
- Formulas are often expressed in *Conjunctive Normal Form (CNF)*

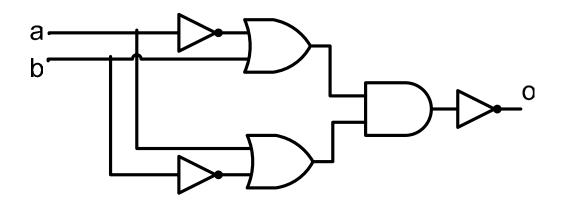




Convert a Boolean Circuit into CNF

• Example: Combinational Equivalence Checking

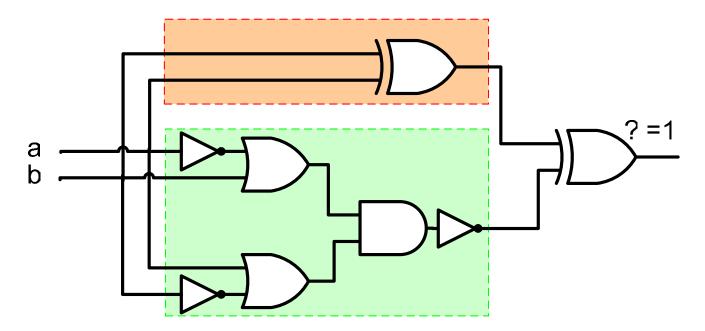






Combinational Equivalence Checking

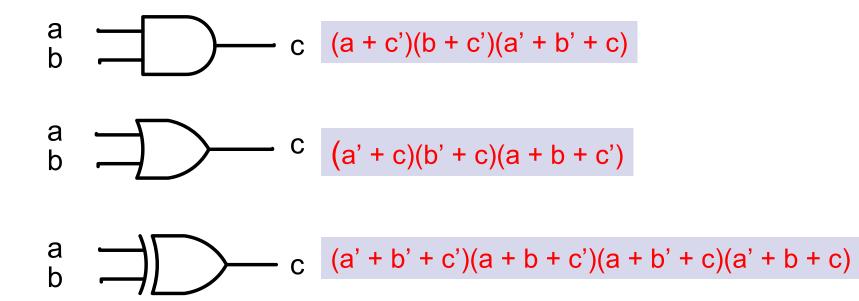
• Miter Circuit





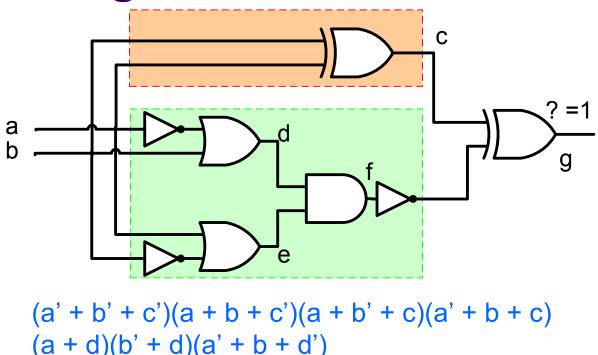
Modeling of Combinational Gates







From Combinational Equivalence Checking to SAT

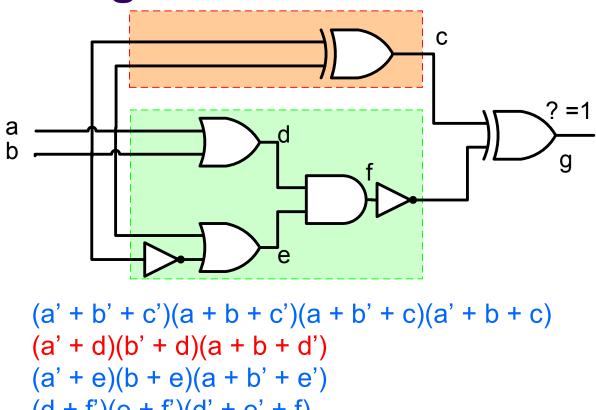




(a' + b' + c')(a + b + c')(a + b' + c)(a' + b + c)(a + d)(b' + d)(a' + b + d') (a' + e)(b + e)(a + b' + e') (d + f')(e + f')(d' + e' + f) (c' + f + g')(c + f' + g')(c + f + g)(c' + f' + g) (g)



From Combinational Equivalence **Checking to SAT**





(d + f')(e + f')(d' + e' + f)(c' + f + g')(c + f' + g')(c + f + g)(c' + f' + g)**(g)**



Convert an Arbitrary Boolean Formula into CNF

- It is possible to convert an arbitrary function into CNF
 - Without introducing new variables, the size of the resulting formula will grow exponentially
 - Not practical
 - By introducing intermediate variables, the size of the resulting formula can grow linearly
 - How?
 - Number of intermediate variable equal to the number of Boolean operations
 - The resulting formula will have the same satisfiability as the original one
- It's sufficient for a SAT solver to solve problems in CNF
 - Almost all modern SAT solver operates on CNF



Complexity of SAT



- A CNF formula is said to belong to *k*-SAT if each clause of the formula contains no more than *k* literals.
- Classic Result:
 - Cook 1971: 3-SAT problem is NP-Complete.
 - NP complete: Class of problems for which no known solutions exists that takes less than O(2ⁿ) steps. However, it has not been proved that the problem needs at least an exponential number of steps. The common conjecture is that it does.
 - k-SAT is NP-complete for $k \ge 3$.
- The obvious lower bound for a SAT problem with n variables is 2^n .
- Currently, the best lower bound for a SAT problem with *n* variables is due to Paturi etc., E.g. for satisfiable 3-SAT, the complexity for finding a solution is O(2^{0.448n}).



SAT Problems with Polynomial Complexity



- Some special SAT classes can be solved in polynomial time.
 - If a problem is solvable in polynomial time, we can use special algorithms to solve them efficiently.
 - Part of the original problem may belong to a polynomial solvable class, it is possible to exploit this property during the solving process. (e.g. Larrabee).
 - During the solution process, a problem state may evolve to one that has a polynomial solution. We can exploit heuristics that are likely to reduce a problem to one that is solvable in polynomial time quickly (e.g. SATO).
- 2-SAT problems can be solved in linear time wrt the size of the problem (Aspvall, Plass and Tarjan, 1979).
- A Horn formula can be solved in linear time wrt the size of the formula.



Horn Formulas

- Horn sentences are often generated from knowledge base reasoning:
 - rules: if x, y, z are true, then r is true
 - $xyz \rightarrow r$
 - $a \rightarrow b$
 - If a is true, then b must be true to make the formula true
 - if a is false, then the formula is true
 - (a' + b)
 - $xyz \rightarrow r$: (x' + y' + z' + r)
- A CNF formula is Horn if every clause has at most one positive literal
 - What does it mean if a clause contains no positive literal?
 - What does it mean if a clause contains only one positive literal and no negative literal?
- A Horn formula can be solved in linear time wrt the size of the formula.
 - Do unit implication until no unit clause exists
 - If conflict, the formula is unsatisfiable
 - Else the formula can be satisfied by assigning all the unassigned variables with value 0







Problem Hardness and Phase Transition



- Not all SAT problems are hard
 - Many practical SAT instances can be solved very efficiently
 - The theory of NP-completeness is based on *worst-case* complexity.
 - To explain the behavior of algorithms in practice, the theory of *average-case* complexity is more appropriate.
- Use random generated SAT instances to explore the hardness distribution
 - Very different characteristics from the instances generated from real world applications
 - But are of great theoretical interests



Fixed-clause length model

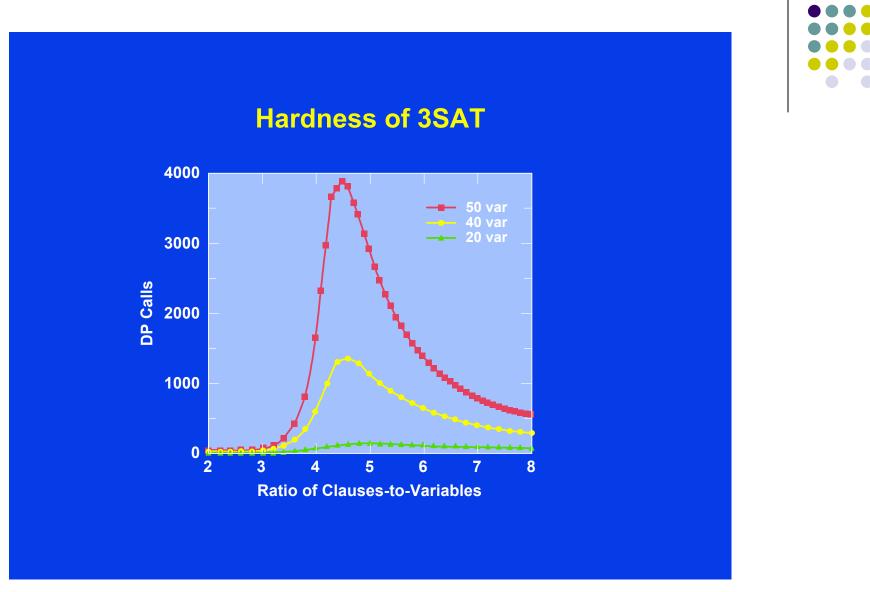
- Generated by selecting clauses uniformly at random from the set of all possible (non-trivial) clauses of a given length, random k-SAT.
- Three parameters: the number of variables N, the number of literals per clause K, and the number of clauses L.
 - Formulas with few clauses: under-constrained (usually satisfiable),
 - Formulas with many clauses: over-constrained (usually unsatisfiable)
 - Both under-constrained and over-constrained problems are much easier than problems of medium length



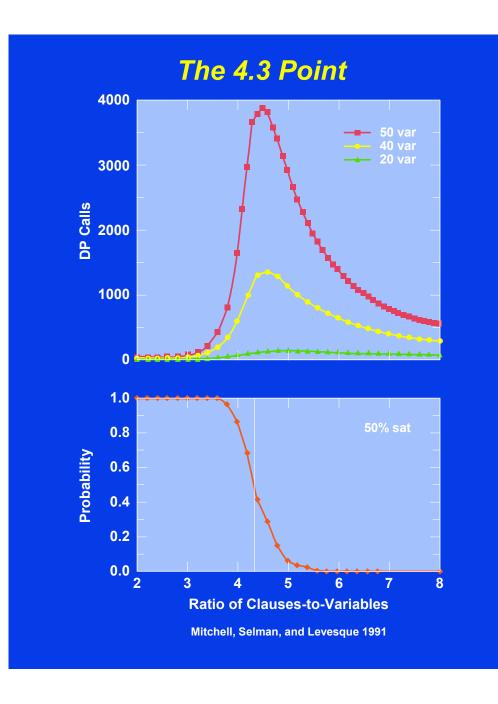
Phase transition behavior

- Problems which are very over-constrained are unsatisfiable and it is usually easy to determine this. Problems which are very under-constrained are satisfiable and it is usually easy to guess one of the many solutions.
- A phase transition tends to occur in between when problems are critically constrained, and it is difficult to determine if they are satisfiable or not.
- For random 2-SAT, the phase transition has been proven to occur at L/N=1.
- For random 3-SAT, the phase transition has been experimentally show to occur around L/N = 4.3







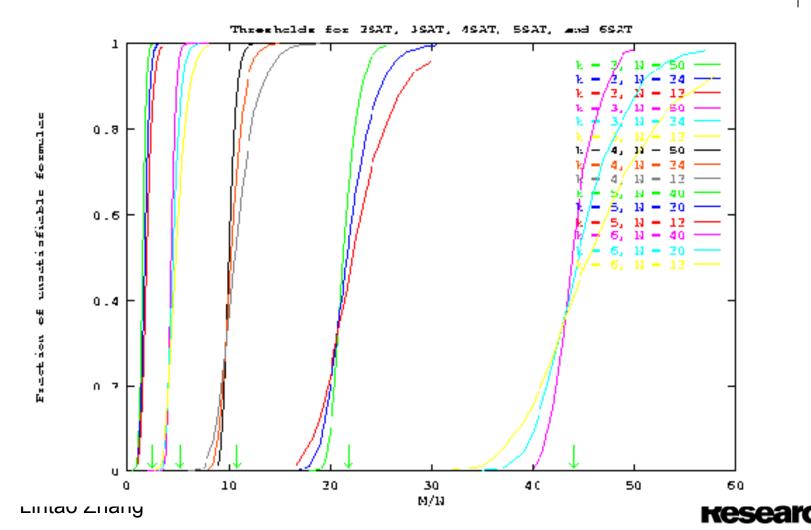






Phase transition 2-, 3-, 4-, 5-, and 6-SAT





Threshold phenomena



- Threshold conjecture: for each k, there is some c* such that for each fixed value of c<c*, random k-SAT with n variables and cn clauses is satisfiable with probability tending to 1 as $n \rightarrow \infty$, and when c>c*, unsatisfiable with probability tending to 1.
- For the case of random 2-SAT, the conjecture has been shown true, and c*=1.
- Current status:
 - 3SAT threshold lies between 3.42 ~ 4.51



The 2+p-SAT model

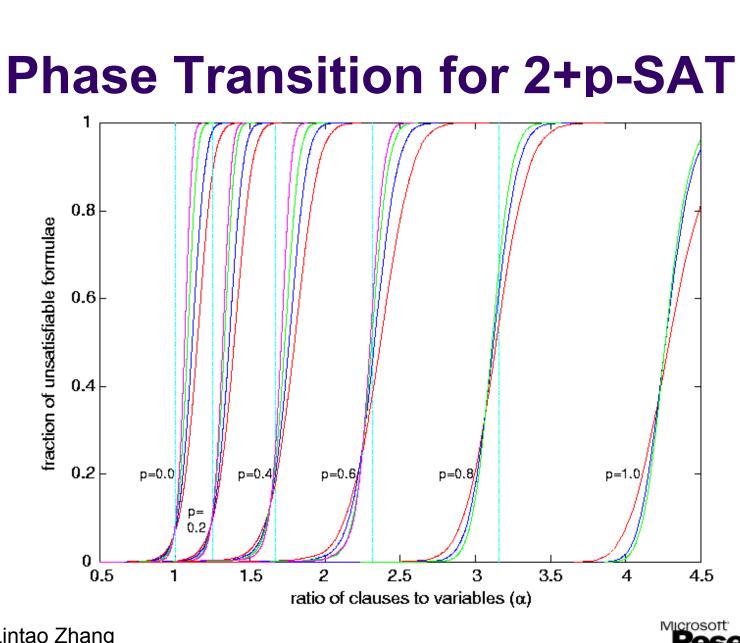
- Mixtures of problem classes, e.g., 2-SAT and 3-SAT ("moving between P and NP")
- Mixture of binary and ternary clauses

p = fraction ternary

p = 0.0 --- 2-SAT / p = 1.0 --- 3-SAT

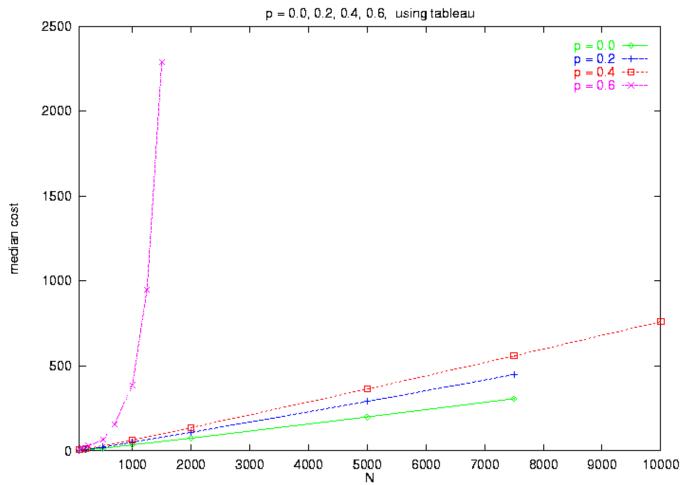
















2+P Model

- p < ~ 0.41 --- model essentially behaves as 2-SAT
 - search proc. "sees" only binary constraints
 - smooth, continuous phase transition
- p > ~ 0.41 --- behaves as 3-SAT (exponential scaling)
 - abrupt, discontinuous scaling







SAT Algorithm: An Overview

- Davis, Putnam, 1960
 - Explicit resolution based
 - May explode in memory
- Davis, Logemann, Loveland, 1962
 - Search based.
 - Most successful, basis for almost all modern SAT solvers
 - Learning and non-chronological backtracking, 1996
- Stålmarcks algorithm, 1980s
 - Proprietary algorithm. Patented.
 - Commercial versions available
- Stochastic Methods, 1992
 - Unable to prove unsatisfiability, but may find solutions for a satisfying problem quickly.
 - Local search and hill climbing





SAT Algorithm: An Overview

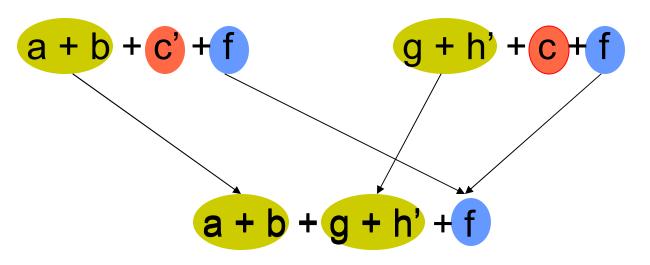
- Davis, Putnam, 1960
 - Explicit resolution based
 - May explode in memory
- Davis, Logemann, Loveland, 1962
 - Search based.
 - Most successful, basis for almost all modern SAT solvers
 - Learning and non-chronological backtracking, 1996
- Stålmarcks algorithm, 1980s
 - Proprietary algorithm. Patented.
 - Commercial versions available
- Stochastic Methods, 1992
 - Unable to prove unsatisfiability, but may find solutions for a satisfying problem quickly.
 - Local search and hill climbing



Resolution



- Resolution of a pair of clauses with exactly **ONE** incompatible variable
 - Two clauses are said to have distance 1
 - (a+b)(a'+c) = (a+b)(a'+c)(b+c)



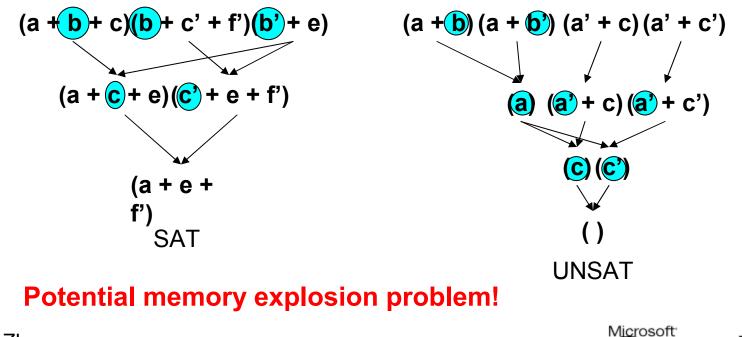


Davis Putnam Algorithm



M .Davis, H. Putnam, "A computing procedure for quantification theory", *J. of ACM*, Vol. 7, pp. 201-214, 1960

- Iteratively select a variable for resolution till no more variables are left.
- Can discard all original clauses after each iteration.



Microsoft Research

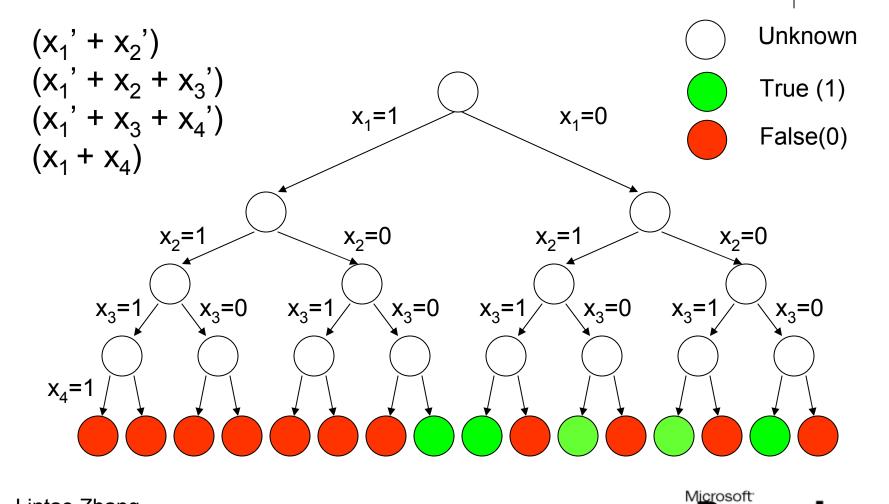


SAT Algorithm: An Overview

- Davis, Putnam, 1960
 - Explicit resolution based
 - May explode in memory
- Davis, Logemann, Loveland, 1962
 - Search based.
 - Most successful, basis for almost all modern SAT solvers
 - Learning and non-chronological backtracking, 1996
- Stålmarcks algorithm, 1980s
 - Proprietary algorithm. Patented.
 - Commercial versions available
- Stochastic Methods, 1992
 - Unable to prove unsatisfiability, but may find solutions for a satisfying problem quickly.
 - Local search and hill climbing



Search Tree of SAT Problem



Deduction Rules for SAT

 Unit Literal Rule: If an unsatisfied clause has all but one of its literals evaluate to 0, then the *free* literal must be implied to be 1.

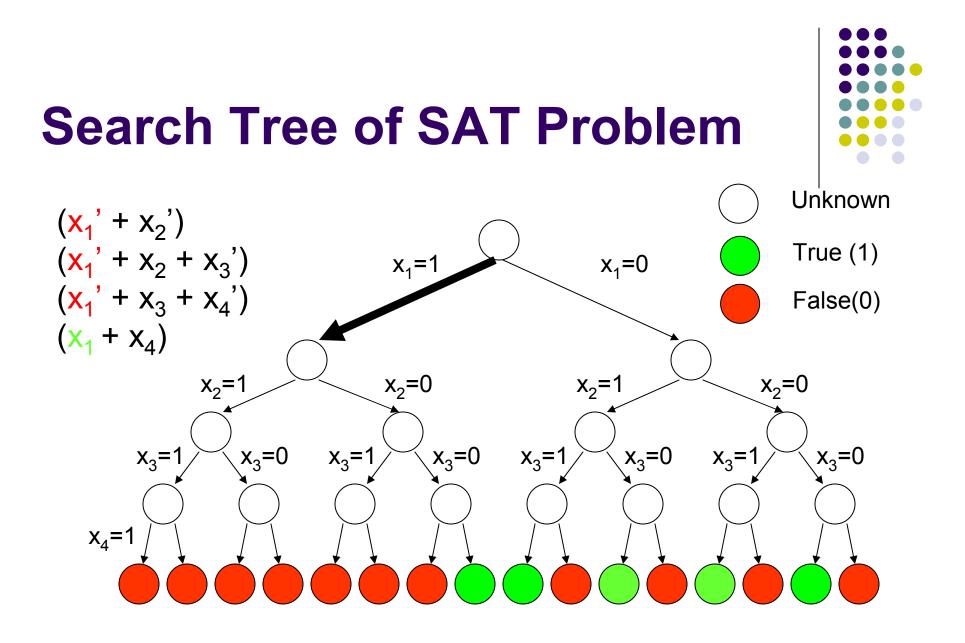
(a + b + c)(d' + e)(a + b + c' + d)

• Conflicting Rule: If all literals in a clause evaluate to 0, then the formula is unsatisfiable in this branch.

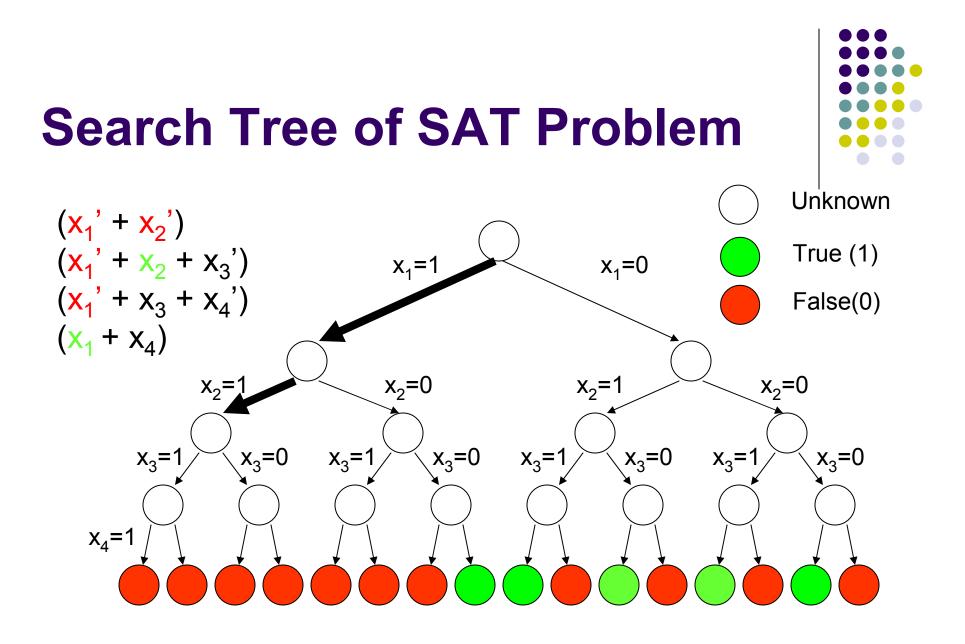
(a + b + c)(d' + e)(a + b + c' + d)



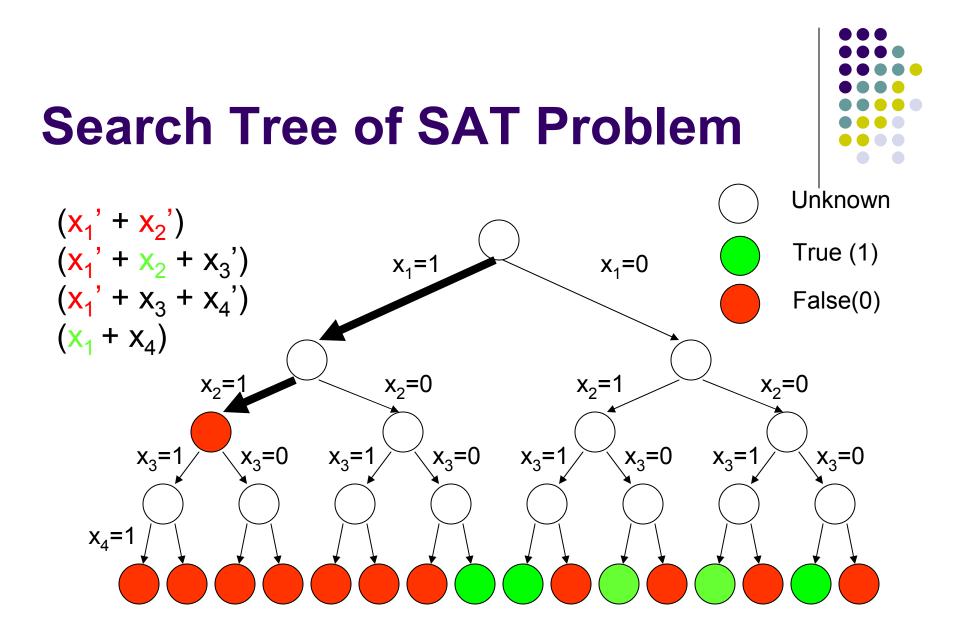




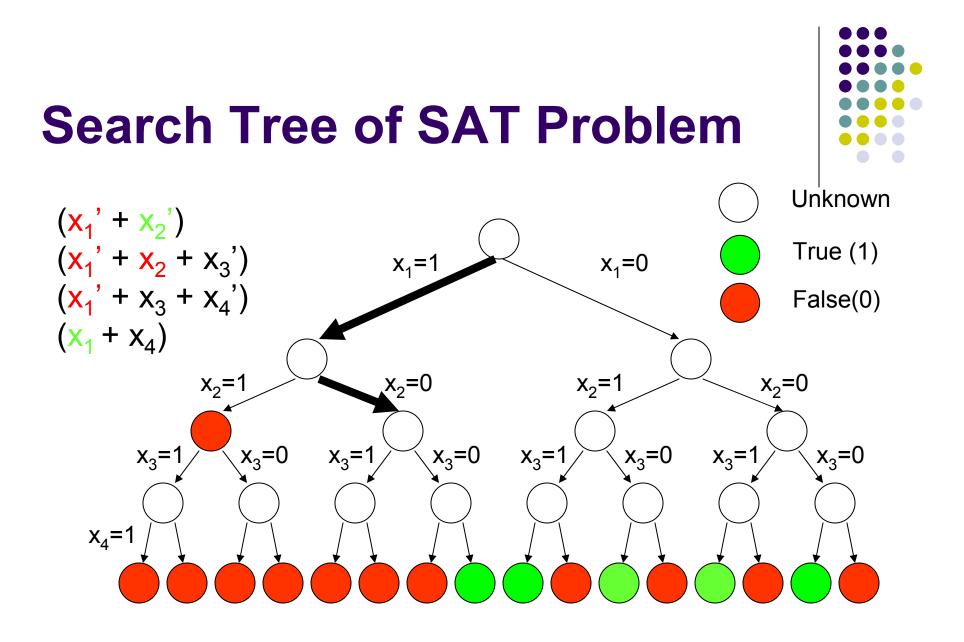




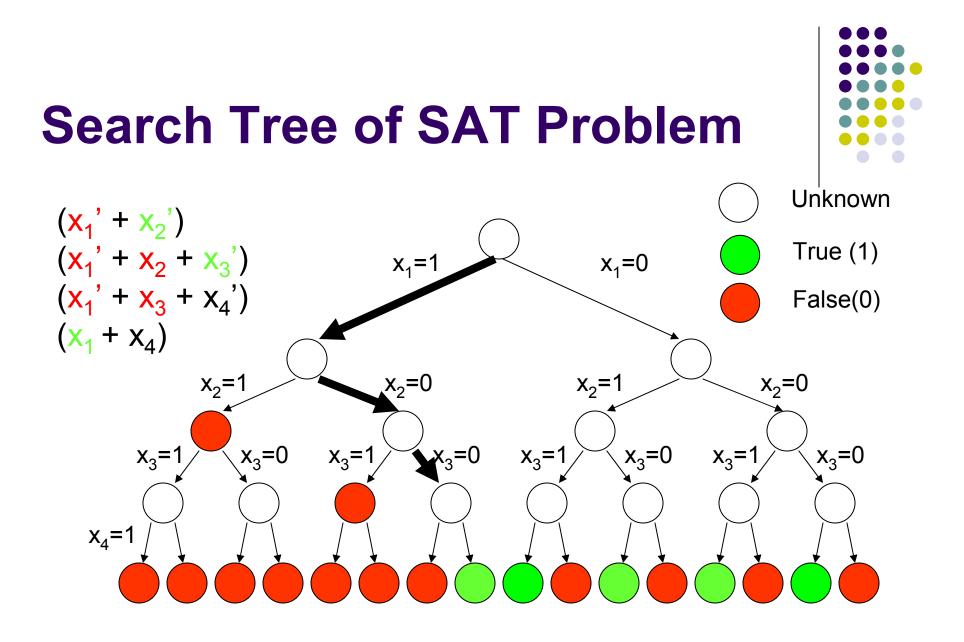
Microsoft[®] Research



Microsoft[®] Research



Microsoft Researc



Microsoft Research

DLL Algorithm



M. Davis, G. Logemann and D. Loveland, "A Machine Program for Theorem-Proving", *Communications of ACM*, Vol. 5, No. 7, pp. 394-397, 1962

- Basic framework for many modern SAT solvers
- Also known as DPLL for historical reasons



(a' + b + c) (a + c + d) (a + c + d') (a + c' + d) (a + c' + d') (b' + c' + d) (a' + b + c') (a' + b' + c)



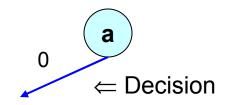


а

(a' + b + c) (a + c + d) (a + c + d') (a + c' + d) (a + c' + d') (b' + c' + d) (a' + b + c') (a' + b' + c)

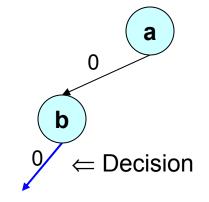
Research

a' + b + c)	
a + c + d)	
a + c + d')	
a + c' + d)	
a + c' + d')	
b' + c' + d)	
a' + b + c')	
a' + b' + c)	





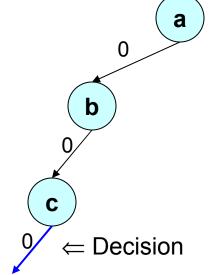
(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)







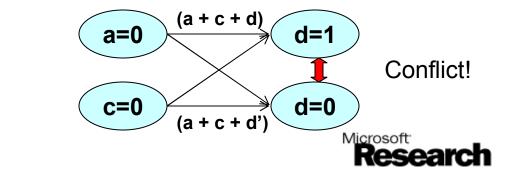
(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)
(



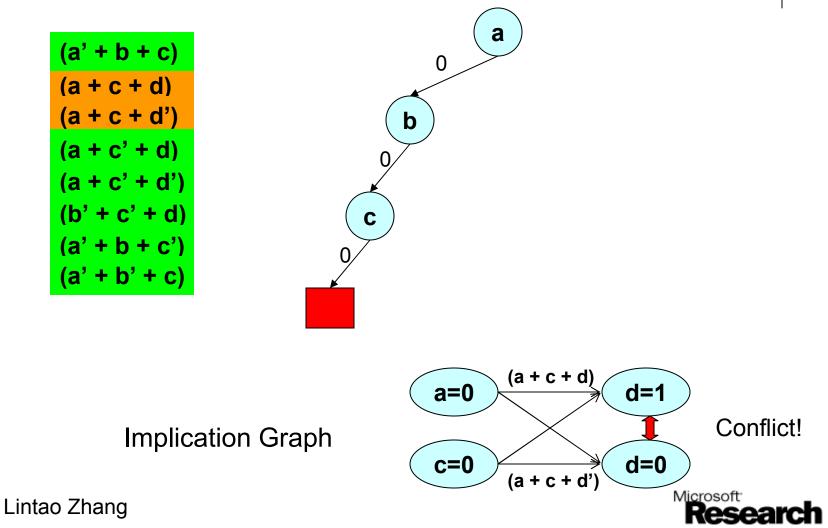




(a' + b + c)	a
(a + c + d)	
(a + c + d')	b
(a + c' + d)	0
(a + c' + d')	
(b' + c' + d)	(c)
(a' + b + c')	0
(a' + b' + c)	

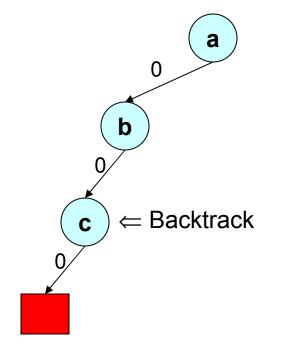


Implication Graph



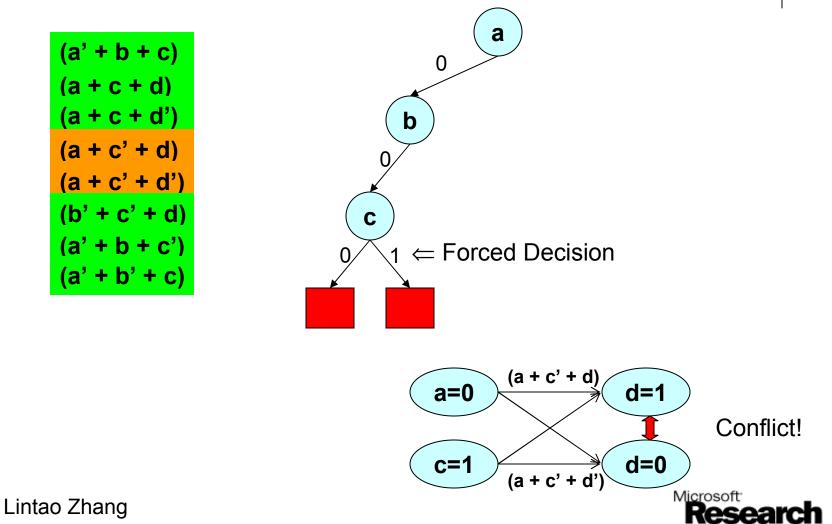


(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)



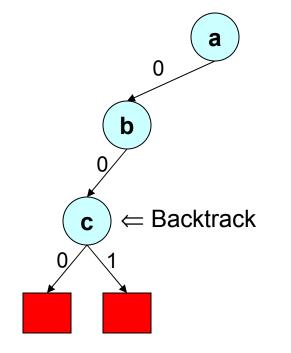








(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)





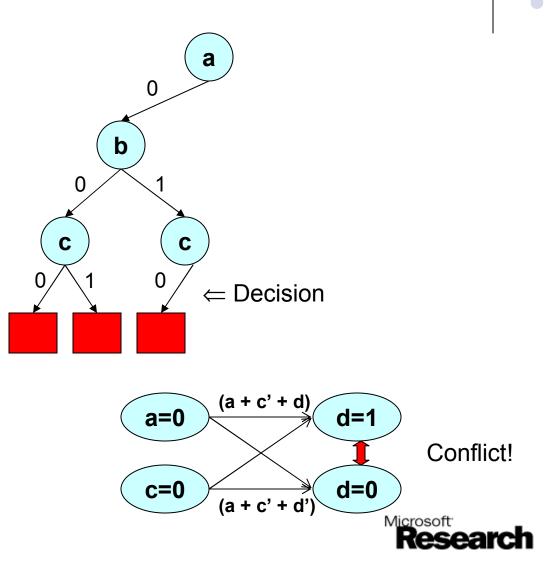


(a' + b + c)	a O
(a + c + d)	
(a + c + d')	b
(a + c' + d)	$0 \times 1 \leftarrow$ Forced Decision
(a + c' + d')	
(b' + c' + d)	(c)
(a' + b + c')	0 1
(a' + b' + c)	

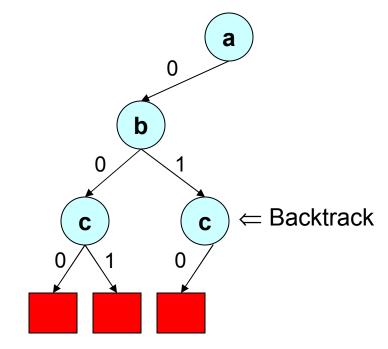




(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)

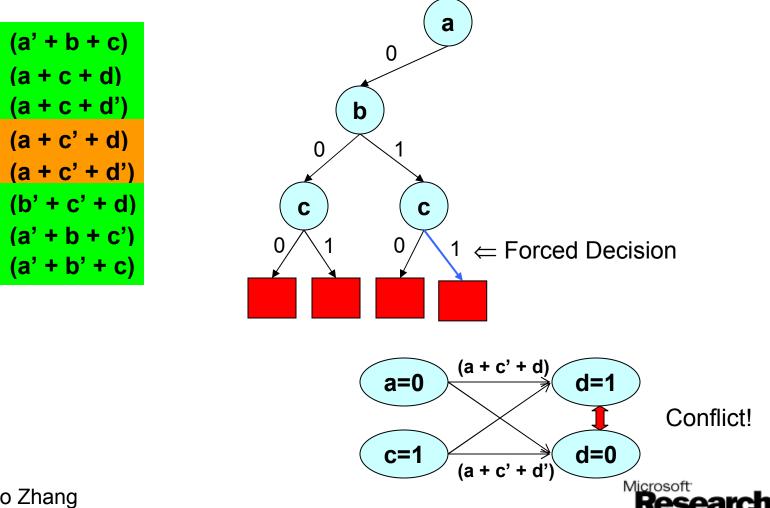


(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)



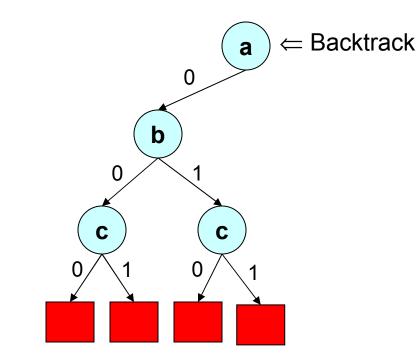








(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)





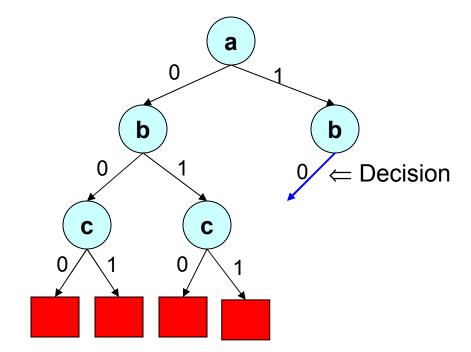
Microsoft[®] Research

(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)





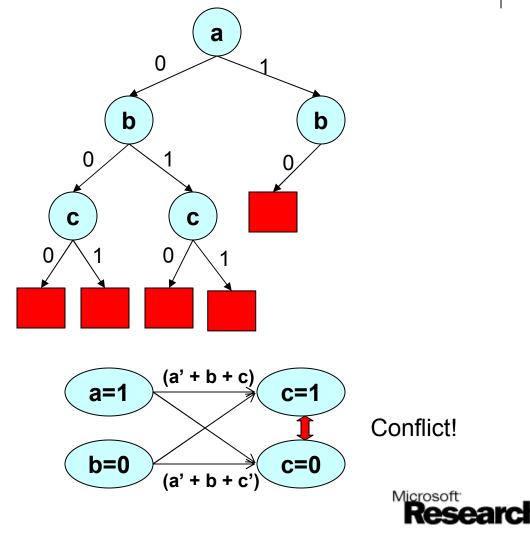
(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)







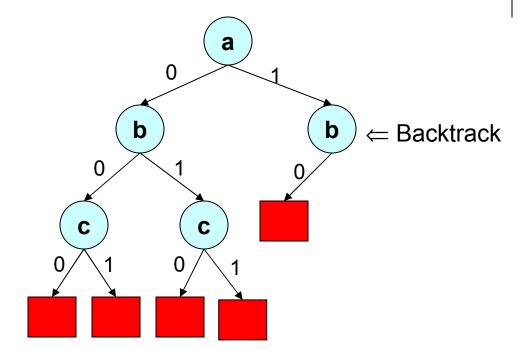
(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)





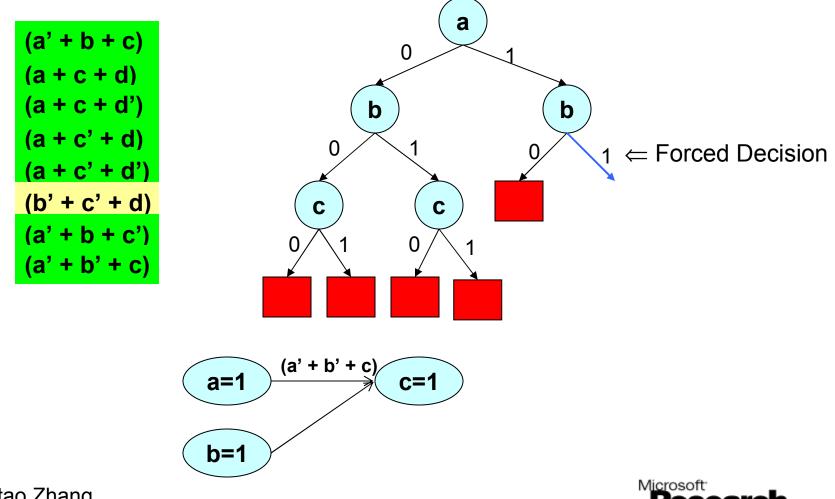


(a' + b + c)
(a + c + d)
(a + c + d')
(a + c' + d)
(a + c' + d')
(b' + c' + d)
(a' + b + c')
(a' + b' + c)

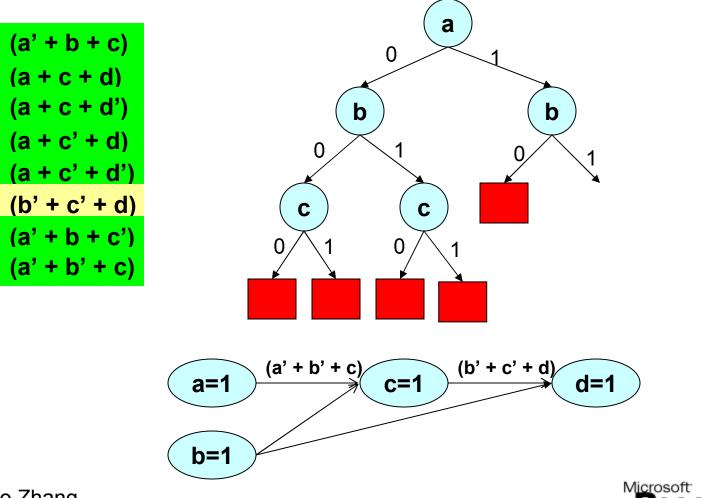




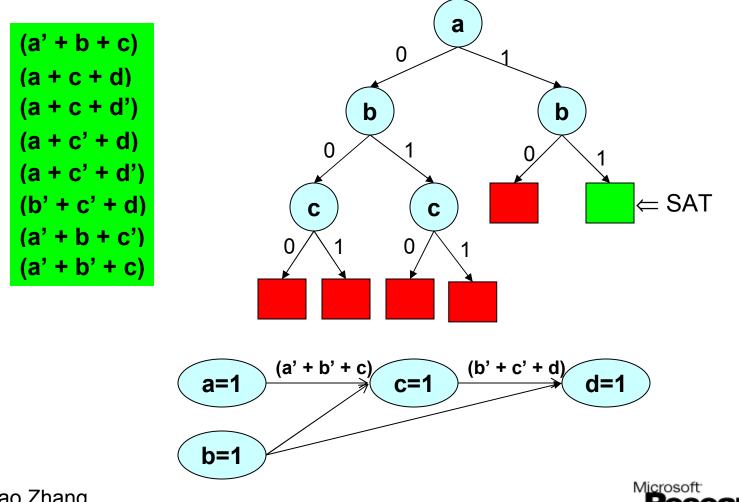














Implications and Boolean Constraint Propagation

- Implication
 - A variable is forced to be assigned to be True or False based on previous assignments.
- Unit clause rule (rule for elimination of one literal clauses)
 - An <u>unsatisfied</u> clause is a <u>unit</u> clause if it has exactly one unassigned literal.

a = T, b = T, c is unassigned

Satisfied Literal Unsatisfied Literal Unassigned Literal

- The unassigned literal is implied because of the unit clause.
- Boolean Constraint Propagation (BCP)
 - Iteratively apply the unit clause rule until there is no unit clause available.
- Workhorse of DLL based algorithms.



Features of DLL

- Eliminates the exponential memory requirements of DP
- Exponential time is still a problem
- Limited practical applicability largest use seen in automatic theorem proving
- The original DLL algorithm has seen a lot of success for solving random generated instances.





Some Notes



- There are another rules proposed by the original DLL paper, which is seldom used in practice
 - Pure literal rule: if a variable only occur in one phase in the clause database, then the literal can be simply assigned with the value *true*
- The original DP paper also included the unit implication rule to simplify the clauses generated from resolution
 - Still may result in memory explosion
- DLL and DP algorithms are tightly related
 - Fundamentally, both are based on the resolution operation





SAT Algorithm: An Overview

- Davis, Putnam, 1960
 - Explicit resolution based
 - May explode in memory
- Davis, Logemann, Loveland, 1962
 - Search based.
 - Most successful, basis for almost all modern SAT solvers
 - Learning and non-chronological backtracking, 1996
- Stålmarcks algorithm, 1980s
 - Proprietary algorithm. Patented.
 - Commercial versions available
- Stochastic Methods, 1992
 - Unable to prove unsatisfiability, but may find solutions for a satisfying problem quickly.
 - Local search and hill climbing



Stålmarck's Algorithm

M. Sheeran and G. Stålmarck "A tutorial on Stålmarck's proof procedure", *Proc. FMCAD*, 1998

- Algorithm:
 - Using triplets to represent formula
 - Closer to a circuit representation
 - Branch on variable relationships besides on variables
 - Ability to add new variables on the fly
 - Breadth first search over all possible trees in increasing depth

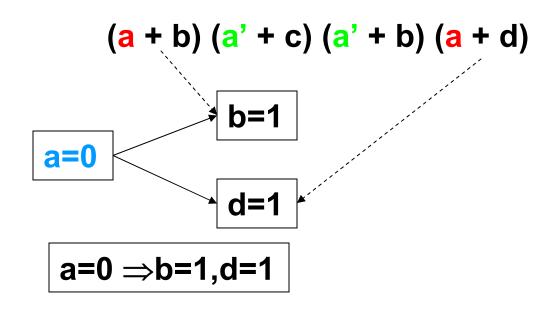


Try both sides of a branch to find forced decisions (relationships between variables)

(a + b) (a' + c) (a' + b) (a + d)

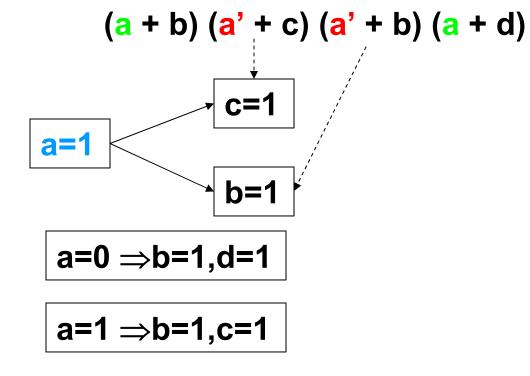


• Try both sides of a branch to find forced decisions





• Try both side of a branch to find forced decisions







• Try both sides of a branch to find forced decisions

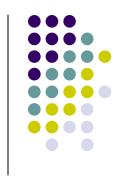
(a + b) (a' + c) (a' + b) (a + d)

$$a=0 \Rightarrow b=1, d=1 \Rightarrow b=2$$
$$\Rightarrow b=2$$
$$a=1 \Rightarrow b=1, c=1$$

- Repeat for all variables
- Repeat for all pairs, triples,... till either SAT or UNSAT is proved









SAT Algorithm: An Overview

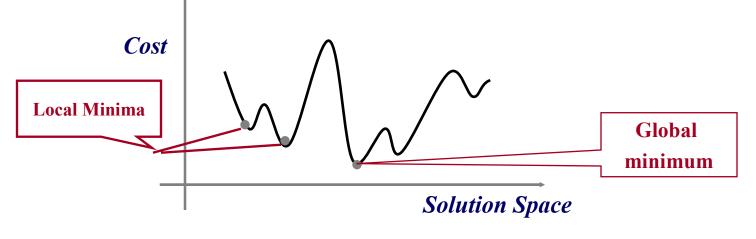
- Davis, Putnam, 1960
 - Explicit resolution based
 - May explode in memory
- Davis, Logemann, Loveland, 1962
 - Search based.
 - Most successful, basis for almost all modern SAT solvers
 - Learning and non-chronological backtracking, 1996
- Stålmarcks algorithm, 1980s
 - Proprietary algorithm. Patented.
 - Commercial versions available
- Stochastic Methods, 1992
 - Unable to prove unsatisfiability, but may find solutions for a satisfying problem quickly.
 - Local search and hill climbing



Local Search (GSAT, WSAT)

B. Selman, H. Levesque, and D. Mitchell. "A new method for solving hard satisfiability problems". *Proc. AAAI*, 1992.

- View the solution space as a set of points connected to each other
- There is cost function which needs to be minimized that can be computed for each point.
- Local search involves starting at some point in the solution space, and moving to adjacent points in an attempt to lower the cost function.
- The search is said to be greedy if it does not ever increase the cost function.







Local Search for Max-SAT

- MAX-SAT:
 - Find an assignment that satisfies the most number of clauses
 - Cost function for a given assignment: number of unsatisfied clauses
- Local search has been shown to work well for MAX-SAT
- Cost function for SAT?
 - Can continue to use number of unsatisfied clauses
 - However, only points with a cost function of 0 are of interest





Algorithm of GSAT

Procedure GSAT for i:= 1 to MAX-TRIES T:= a randomly genrated truth assignment for j:= 1 to MAX-FLIPS if T satisfies α then return T flip the variable that results in the greatest decrease in the number of unsatisfied clauses (decrease ≥ 0) end for end for

return "No satisfying assignment found"

- decrease = 0 is referred to as a "sideways" move
- sequence of sideways moves is a "plateau"
- success depends on ability to move between successively lower plateaus



Properties of GSAT

- Seems to work well on randomly generated 3-CNF problems
- Can get stuck in a local minima
- Not guaranteed to be complete

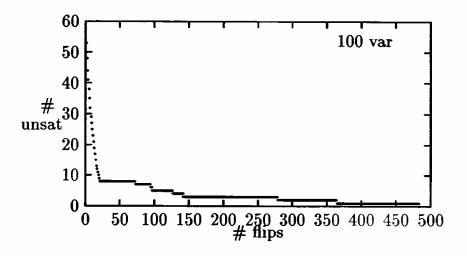


FIGURE 1. GSAT's search space on a randomly-generated 100 variable 3CNF formula with 430 clauses.





Getting out of Local Minima

- Random Walk Strategy
 - with probability p, pick a variable occuring in some unsatisfied clause and flip its assignment;
 - with probability (1-p), follow the standard GSAT scheme, i.e make the best possible local move
- Random Noise Strategy
 - similar to random walk, except that do not restrict the variable to be flipped to be in an unsatisfied clause
- Simulated Annealing
 - make random flips
 - probabilistically accept "bad moves"



Conclusions about Local Search

- Many local search algorithms exists
 - GSAT, WalkSAT, DLM etc.
 - Differs on how to get out of local minimum
- Incomplete, unable to prove unsatisfiability
 - How to make local search complete is still an open question
- Can be vastly superior than systematic search based algorithms on certain satisfiable formulas
- Has some application in AI planning, limited use in EDA or formal verification

