Lecture 4

Polynomial-time formula classes

Horn-SAT, 2-SAT, X-SAT, Walk-SAT

Introduction to Logic for Computer Science

Prof Hongseok Yang KAIST

These slides are minor variants of those made by Prof Worrell and Dr Haase for their logic course at Oxford.

Recap and some additional notation

 A literal is a propositional variable or the negation of a propositional variable:

$$x$$
 or $\neg x$.

- We call x a positive literal and $\neg x$ a negative literal.
- A disjunction of literals is a clause.
- A formula F is in conjunctive normal form (CNF) if it is a conjunction of disjunctions of literals L_{i,j}:

$$F = \bigwedge_{i=1}^{n} \left(\bigvee_{j=1}^{m_i} L_{i,j} \right).$$

 Convention: true is CNF with no clauses, false is CNF with a single empty clause without literals.

Agenda

Polynomial-time fragments of propositional logic

Walk-SAT: A randomised algorithm for satisfiability

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But, we can often do better for formulas of special form:

- Horn formulas: SAT can be decided in polynomial time.
- 2-CNF formulas: SAT can be decided in polynomial time.
- X-CNF formulas: SAT can be decided in polynomial time.

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 Horn formulas can be rewritten in a more intuitive way as conjunctions of implications, called implication form. E.g.:

$$(\textit{true} \rightarrow \textit{p}_1) \land (\textit{p}_2 \land \textit{p}_3 \rightarrow \textit{false}) \land (\textit{p}_1 \land \textit{p}_2 \rightarrow \textit{p}_4).$$

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 Many applications in computer science. Prolog and Datalog are based on Horn formulas.

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 $\text{Unsat.: } (\textit{true} \rightarrow \textit{p}_1) \land (\textit{p}_2 \land \textit{p}_3 \rightarrow \textit{false}) \land (\textit{p}_1 \rightarrow \textit{p}_2) \land (\textit{p}_1 \land \textit{p}_2 \rightarrow \textit{p}_3).$

Horn-SAT algorithm

Idea:

- Maintain an assignment ${\mathcal A}$ for propositional variables, starting with $p\mapsto 0$.
- Update A(p) from 0 to 1 if forced by F, until either F is satisfied or contradiction is reached.

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Ex: Why correct?

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- Loop invariant: If \mathcal{B} satisfies F, then $\mathcal{A} \leq \mathcal{B}$.
- Ex1: Prove that this is a loop invariant.
- Ex2: Prove that this loop invariant gives the desired result.

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- The **implication graph** of a 2-CNF formula F is a directed graph $\mathcal{G} = (V, E)$, where

$$V:=\left\{ p_{1},\ldots,p_{n}\right\} \cup\left\{ \neg p_{1},\ldots,\neg p_{n}\right\} ,$$

with p_1, \ldots, p_n prop. variables mentioned in F.

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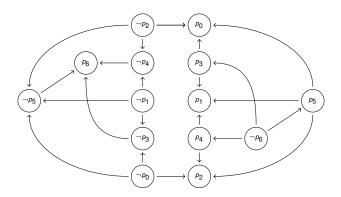
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- Ex: If (L, M) is an edge, is $(\overline{M}, \overline{L})$ also an edge?

2-CNF formulas: example

$$(p_0 \lor p_2) \land (p_0 \lor \neg p_3) \land (p_1 \lor \neg p_3) \land (p_1 \lor \neg p_4) \land (p_2 \lor \neg p_4)$$
$$\land (p_0 \lor \neg p_5) \land (p_1 \lor \neg p_5) \land (p_2 \lor \neg p_5) \land (p_3 \lor p_6) \land (p_4 \lor p_6) \land (p_5 \lor p_6)$$

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• Paths in \mathcal{G} correspond to chains of implications.

- Can reduce satisfiability for 2-CNF formulas to reachability problem of implication graph, which is solvable in poly. time.
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(⇐) Construct a satisfying assignment. Ex: How?

2-SAT Algorithm

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INPUT: 2-CNF formula F
\mathcal{A}:= empty (partial) assignment
while there is some unassigned variable do
begin
pick a literal L for which there is no path from L to \overline{L}
set \mathcal{A}(L):=1
while there is an edge (M,N) with \mathcal{A}(M)=1 and \mathcal{A}(N) is undefined
do \mathcal{A}(N):=1
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Ex: Why correct? Invariants for the outer and inner loops?

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- Inner loop maintains the invariant. So when it terminates, every node reachable from a true node is true.

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Proof.

List all subformulas of $F: F_1 = p_1, \dots, F_m = p_m, F_{m+1}, \dots, F_n$.

Introduce new variables p_{m+1}, \ldots, p_n .

Associate formulas G_i asserting $p_i \leftrightarrow F_i$.

Take
$$G = G_{m+1} \wedge \cdots \wedge G_n \wedge p_n$$
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- An X-CNF formula is a conjunction of XOR-clauses.

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Can solve these equations using **Gaussian elimination**.

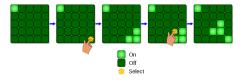
Lights out

Given: An $N \times N$ grid, each button coloured black or white.

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Ex: Translate this to X-SAT.



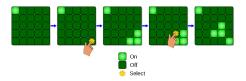
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Hint1: Even number of same moves doesn't do anything.

Hint2: Let $p_{i,j}$ denote whether the button (i,j) is pressed, and $c_{i,j}$ be the initial colour of the button (i,j), where $c_{i,j} = true$ means black.

Polynomial-time fragments of propositional logic

Walk-SAT: A randomised algorithm for satisfiability

Randomised algorithm for solving SAT for CNF formulas F.

- Guess an assignment for F uniformly at random.
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Theorem: Walk-SAT on *n*-variable satisfiable 2-CNF formula for $r = 2mn^2$ succeeds with probability $\geq 1 - 2^{-m}$.

Walk-SAT: algorithm precisely

Input: CNF formula *F* with *n* variables, repetition parameter r

pick an assignment (to the n variables) uniformly at random if F is satisfied **then** return the current assignment **repeat** r times

pick an unsatisfied clause pick a literal in the clause uniformly at random, and flip value if F is satisfied **then** return the current assignment **return** UNSAT

By assignments, we mean maps from the variables in F to $\{0,1\}$.

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$$T_0 = 0,$$
 $T_n = 1 + T_{n-1},$ $T_i \le 1 + (T_{i+1} + T_{i-1})/2.$

Ex: Why do these relationships hold?

• Replacing inequalities by equalities gives bound $H_i \ge T_i$:

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Ex: Why $H_i > T_i$? Prove it.

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- **Theorem**: Walk-SAT on *n*-variable satisfiable 2-CNF formula for $r = 2mn^2$ succeeds with probability $\geq 1 2^{-m}$.

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- n+1 linearly independent eqs in n+1 unknowns. Ex: Show that the unique solution is $H_i = (2i \cdot n) - i^2$. So the worst expected time to hit \mathcal{A} is $H_n = n^2$.
- Markov's inequality: If X is a nonnegative random variable, then $\mathbb{P}[X \ge a] \le \frac{1}{a}\mathbb{E}[X]$ for all a > 0.
- **Theorem**: Walk-SAT on *n*-variable satisfiable 2-CNF formula for $r = 2mn^2$ succeeds with probability $\geq 1 2^{-m}$.

Proof: Divide $2mn^2$ iterations of the main loop into m phases. Markov: not finding a satisfying assignment in a phase has probability $\leq n^2/2n^2 = 1/2$.

What's bad about 3-SAT?

 Common feature of Horn-SAT and 2-SAT algorithms: build satisfying assignments incrementally, without backtracking. This is different for general CNF formulas.

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- Common feature of Horn-SAT and 2-SAT algorithms: build satisfying assignments incrementally, without backtracking. This is different for general CNF formulas.
- Walk-SAT: one-dimensional random walk on line $\{0, ..., n\}$ with absorbing barrier 0 and reflecting barrier n.

Similar trick for 3-CNF formulas with probability 2/3 of going right and 1/3 of going left

However, then r needs to be exponential in n.

Summary

- SAT is bad, but we can do better in special cases.
- Horn-SAT, 2-SAT and X-SAT can be solved by polynomial-time algorithms.
- But 3-SAT is as "bad" as the satisfiability of the entire propositional logic.