A #SAT Algorithm for Small Constant-Depth Circuits with PTF gates.

Nutan Limaye

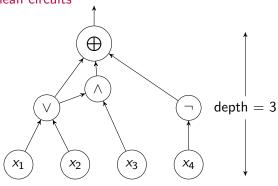
Computer Science and Engineering Department, Indian Institute of Technology, Bombay, (IITB) India. Joint work with

Swapnam Bajpai, Vaibhav Krishan, Deepanshu Kush, and Srikanth Srinivasan. IIT Bombay, India.

Complexity, Algorithms, Automata and Logic Meet (CAALM 2019) Chennai Mathematical Institute, January 2019.

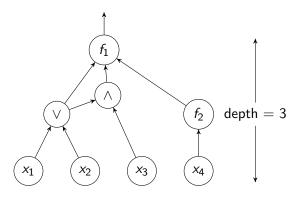
Circuit satisfiability algorithms Boolean circuits





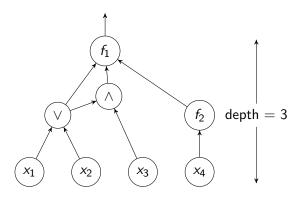
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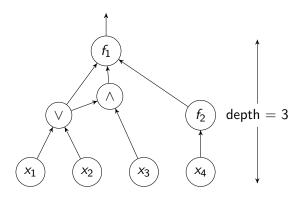
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Number of input variables: n

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Constant-depth circuits: d is independent of n.

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Can we design an algorithm that takes time $2^n/n^{\omega(1)}$ when |C| is small, say $\operatorname{poly}(n)$?

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Better than brute-force circuit-satisfiability algorithms for a class $\mathcal C$ reveals some weaknesses of functions computable by $\mathcal C$.

This intuitive connection has been formalised to derive lowerbounds for various interesting classes of circuits.

[Paturi, Pudlák, Zane 1997],[Paturi, Pudlák, Saks, Zane 2005], [Williams 2010], [Williams 2011].

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A function $f: \{-1,1\}^n \to \{-1,1\}$ is called a degree-k Polynomial Threshold Function (k-PTF) if there is a multilinear degree-k polynomial

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Example: $AND(x_1, x_2) = sign(x_1 + x_2 + 1) = sign(100x_1 + 100x_2 + 1)$.

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Polynomial Threshold circuits are a natural generalization of TC⁰.

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Fix any constant k, there is a zero-error radomized algorithm that solves the #SAT problem for a single k-PTF in time $\operatorname{poly}(n,M) \cdot 2^{n-s}$, where $s = \tilde{\Omega}(n^{1/k+1})$.

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Some comments on zero-error randomized algorithms.

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If look-up can be done in $\operatorname{poly}(|C|)$ time, then this step takes time $O(2^{n-m} \cdot \operatorname{poly}(|C|)) \ll 2^n$.

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Every k-PTF on m variables can be sign represented by a polynomial with coefficients bounded by $2^{O(\text{poly}(m))}$. [Muroga 1971].

Simply store all polynomials with small weights in the table.

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Expensive to compute

Even for LTFs computing Chow parameters is known to be NP-hard. [O'Donnell, Servedio 2011].

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Small depth decision tree for this implies a fast learning algorithm.

Definition

Given a k-PTF P' on m variables, let $\operatorname{coeff}(P') \in \mathbb{R}^r$ denote a vector of coefficients of all monomials in P' in lexicographical order, where $r = \sum_{i=0}^k \binom{m}{i}$.

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This produces a decision tree T that has the following properties: Each internal node of the tree is a linear test $(\sum_{i=1}^{r} \alpha_i w_i \ge \theta)$, where w_i s are the inputs and $\alpha_i \in \{-2, -1, 0, 1, 2\}$.

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Memoization for k-PTF

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Time: $\exp(m^{k+1}) + 2^{n-m} \operatorname{poly}(n, M) = 2^{n-m} \operatorname{poly}(n, M)$ if $m = n^{1/k+1}/\log n$.

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Develop strategies that work for these two steps even when the k-PTF gates are not sparse.

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Some techniques in this talk could be of general interest!

Better than brute-force algorithms for

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Constant depth k-PTF circuits with slightly superlinear size.

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Can this technique inspire any SAT solving heuristic?

Thank You!