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

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

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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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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 $poly(n, M) \cdot 2^{n-s}$, 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 poly(|C|) time, then this step takes time $O(2^{n-m} \cdot poly(|C|)) \ll 2^n$.

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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 $r = \sum_{i=0}^{k} {m \choose i}$.

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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!