

# Approximation of constraint satisfaction problems

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May 17, 2008

# Questions please!

We are from different fields so our perspectives are probably different.

Interaction is a great invention.

Please ask questions!

Will tell a story, few technical details and not many references.

Will not live up to title and hardly get beyond 3-Sat.

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Interested in provable properties.

Our favorite problem is 3-Sat

$$(\bar{x}_1 \vee x_7 \vee x_{11}) \wedge \dots (x_4 \vee \bar{x}_9 \vee x_{25})$$

Most of the time not random.

Each clause of length 3.

Usually  $n$  variables,  $m$  clauses.



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Let us look into algorithms that do reasonably well for each input.

We define

$$\alpha = \frac{\text{Number of satisfied constraints}}{\text{Optimal number of satisfied constraints}}$$

worst case over inputs, expected over internal randomness if we have a probabilistic algorithm.

# Trivial approximation ratio

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We get an approximation ratio of  $7/8$  which is the trivial approximation ratio.

# My favorite problem

Similarly we get a trivial approximation ratio for other problems. Comparing the number of constraints satisfied by a random assignment to all constraints.

For which type of constraints can we do better?

# A problem on randomized Sat

Suppose we have random 3-Sat formula, fairly dense and hence probably not satisfiable.

We want a polynomial time algorithm that is allowed to answer “satisfiable”, “not satisfiable” and “don't know” and never is allowed to be incorrect.

For what values of  $m$  can the algorithm decide most formulas?

An approximation algorithm with  $\alpha$  a constant greater than  $7/8$  would give a positive result for any  $m = \omega(n)$ .

This follows as for such  $m$  the best assignment satisfies  $(7/8 + o(1))m$  clauses.



# State of knowledge for this problem

Best results handle  $m = c \cdot n^{3/2}$ , no consensus of correct answer.

Nice problem to think about!

# Minimal hope for approximation

A promise problem for some  $\epsilon > 0$ .

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Theorem [H]: For any  $\epsilon > 0$  it is NP-hard to tell which of the two is the case.

Theorem: For any  $\epsilon > 0$  it is NP-hard to approximation Max-3-Sat within  $7/8 + \epsilon$ .

It is NP-hard to beat the trivial approximation ratio.

Max-3-Sat is **approximation resistant**.

# NP-hard?

A problem is NP-hard if solving it in polynomial time implies that  $NP=P$ .

Thus the same property as being NP-complete, but we do not require the problem to belong to NP.

# Proving the theorem

Proof on high level. Given a formula  $\varphi$  we, in polynomial time, produce a formula  $\psi$  such that.

If  $\varphi$  is satisfiable so is  $\psi$ .

If  $\varphi$  is not satisfiable then no assignment satisfies more than a fraction  $7/8 + \epsilon$  of the clauses of  $\psi$ .

The formula  $\psi$  satisfies the promise and distinguishing the two cases is equivalent to determining whether  $\varphi$  is satisfiable.

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Creating  $\psi$  is a long story, let us tell a tiny part.

A proof is checked by a (polynomial time) verifier  $V$ .

In a standard proof  $V$  reads the entire proof and is certain of its validity.

Instance: A formula  $\varphi$ , claimed to be satisfiable.

Proof: A satisfying assignment to  $\varphi$ .

Checking: Substituting the assignment in  $\varphi$  and making sure that it is satisfied.

$V$  runs in deterministic polynomial time.

$V$  reads the entire proof which is of polynomial size.

$V$  is never fooled to accept an incorrect claim or an incorrect proof of a correct claim.

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This is a **Probabilistically Checkable Proof (PCP)**.

# Remember our reduction

Given  $\varphi$  we efficiently produce  $\psi$  such that:

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A (satisfying) assignment to the variables of  $\psi$  gives a PCP!

# The basic PCP

Given  $\psi$ , satisfiable or at most  $(7/8 + \epsilon)$  satisfiable.

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Completeness 1, soundness  $7/8 + \epsilon$ , reading 3 bits.

# Getting this ultimate PCP

Obviously (I hope) our final reduction has magical properties on top of proving the theorem.

Would be too much to hope for to simply write it down and check in a couple of slides.

The PCP theorem [Arora, Lund, Motwani, Sudan and Szegedy, 1990]: It is possible to check satisfiability by a polynomial size proof, that reads  $O(1)$  bits, has completeness 1 and soundness  $1/2$ .

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Gives the qualitatively correct statement but constants originally were not so good.

A complicated construction, using many tools.

- Coding an assignment by a lower degree polynomial over a larger domain.
- Properties of low-degree polynomials. Testing that a table is a low degree function.
- Recursive techniques, a proof that there is a proof that there is a proof.

Obtained in 2006.

A (mostly) combinatorial proof relying on recursive construction with expander graphs.

Builds on experience in designing PCPs accumulated over time.



Additional levels of recursion.

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Coding  $t$  bits as  $2^{2^t}$  bits, where  $t$  is some constant.

# A key analysis tool

Use the Fourier transform to analyze Boolean functions.

Early results use simple properties of the Fourier transform.

Recent results rely on strong results in the real domain.

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Pick random  $x$  and  $y$  and check if  $T(x) + T(y) = T(x + y)$  [BLR].

If test accepts with probability  $1 - \delta$  then exists linear function  $L$  that that  $T(x) = L(x)$  for a fraction  $1 - \delta$  fraction of  $x$ .

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Entering these constructions would take us to far..



# Other types of constraints

Can prove similar results for other constraints.

Given linear equations mod  $p$  for a prime  $p$  it is NP-hard to distinguish systems where we can satisfy a fraction  $1 - \epsilon$  of the equations from those where we can only satisfy a fraction  $1/p + \epsilon$ .

Exists many inapproximability results.

Many predicates are approximation resistant.

Many predicates are not, key technique is semidefinite programming.

Interesting proofs that can be checked very efficiently.