Sum-of-Squares Algorithm

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• Given $f: \{\pm 1\}^n \to \mathbb{R}$,

verify if $f \ge 0$, i.e., $f(x) \ge 0$ for all $x \in \{\pm 1\}^n$.

- $\{\pm 1\}^n$ is called a hypercube
 - I found out that {0,1} is more widely used definition for a hypercube...
 But note that there is no difference .

• Given $f: \{\pm 1\}^n \to \mathbb{R}$,

efficiently verify if $f \ge 0$, i.e., $f(x) \ge 0$ for all $x \in \{\pm 1\}^n$.

- $\{\pm 1\}^n$ is called a hypercube
- "Given f" = Given a vector of coefficients of f
 - but... there are infinite number of representation of f...

Multilinear Reduction

- Reduction: $x_i^{\text{odd}} \rightarrow x_i$ and $x_i^{\text{even}} \rightarrow 1$.
- After the reduction, we can view f as a vector $\hat{f} \in \mathbb{R}^{2^n}$ where $\hat{f}(S)$ is the coefficient of $\prod_{i \in S} x_i$.

• Fact. Regardless of representation of f, the reduction outputs a unique vector \hat{f} , which implies $f \equiv f'$ iff $\hat{f} \equiv \hat{f'}$.

Multilinear Reduction

• If the input f satisfies $\deg(f) \le d$ (after the reduction), the dimension of \hat{f} can be $\sum_{i=0}^{\ell} \binom{n}{i} \le (d+1)n^d = n^{O(d)}$.

• Given $f: \{\pm 1\}^n \to \mathbb{R}$ s.t. $\deg(f) \le d$, efficiently verify if $f \ge 0$, i.e., $f(x) \ge 0$ for all $x \in \{\pm 1\}^n$.

- $\{\pm 1\}^n$ is called a hypercube
- "Given f" = "Given \hat{f} of f (WLOG)"

• Given $f: \{\pm 1\}^n \to \mathbb{R}$ s.t. $\deg(f) \le d$ and has rational coeffs., efficiently verify if $f \ge 0$, i.e., $f(x) \ge 0$ for all $x \in \{\pm 1\}^n$.

- $\{\pm 1\}^n$ is called a hypercube
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• Given $f: \{\pm 1\}^n \to \mathbb{R}$ s.t. $\deg(f) \le d$ and has rational coeffs., efficiently verify if $f \ge 0$

(Our) Application: Max-Cut Problem

- Let $f_G(x) \coloneqq \frac{1}{4} \sum_{(i,j) \in E} (x_i x_j)^2$ be the function over $\{\pm 1\}^{|V|}$.
 - find a bipartition of vertices; count the #edges on the cut.
- We want to find x^* that maximizes $f_G(x)$.
- Or... we want to find the smallest c s.t. $c f_G(x) \ge 0$.
- Naive randomized alg.: for each $i \in V$, assign +1 or -1 u.a.r.
 - |E|/2 number of edges are on the cut (in expectation)

(Athor) Applications

- Graph densities; flag algebras (Cauchy-Schwarz proof);
- Quantum information
- and so on...

SoS (Sum-of-Squares) Certificate

d is even

• <u>A degree *d* SoS certificate for *f* is</u>

a list of polynomial functions $g_1, \ldots, g_r: \{\pm 1\}^n \to \mathbb{R}$ s.t.

- $\deg(g_i) \le d/2$ for all i = 1, ..., r and e.g., $\deg(x_1x_3x_7 + x_2x_7 + 2) = 3$
- $f(x) = g_1^2(x) + \dots + g_r^2(x)$ for all $x \in \{\pm 1\}^n$.

To Answer the Problem with SoS Cert...

- Suppose someone gives a degree d SoS certificate g_1, \ldots, g_r .
- Does this efficiently verify $f \ge 0$?
- Requirement:
 - d and r should not be too large.
 - #bits needed to represent coeffs. of g_i should not be too large.
 - Testing $f = g_1^2 + \dots + g_r^2$ is done efficiently.
 - Note that testing for all $x \in \{\pm 1\}^n$ is not efficient.

To Answer the Problem with SoS Cert...

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 - Testing $f = g_1^2 + \dots + g_r^2$ is done efficiently.
 - Compare the coeffs. of $\sum g_i^2$ after the multilinear reduction ($n^{O(d)}$ comparisons)

Does $f \ge 0$ always have a SoS cert.?

- Yes, but with high degree.
- There exists a deg 2n SoS cert. of $f \ge 0$ where $f: \{\pm 1\}^n \to \mathbb{R}$.
- Consider $g \coloneqq \sqrt{f}$.

Since f has degree at most n WLOG, g is a deg 2n SoS cert.

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• WRONG... since g can be non-polynomial.

Does $f \ge 0$ always have a SoS cert.?

• Correct proof) Consider $\{g_z\}_{z \in \{\pm 1\}^n}$ s.t. $g_z(x) = f(z)$ iff x = z.

• Then
$$\sum_{z \in \{\pm 1\}^n} g_z^2 = f$$
.

• Let
$$g_z(x) \coloneqq \sqrt{f(z) \left(\frac{1+z_1 x_1}{2}\right)^2 \left(\frac{1+z_2 x_2}{2}\right)^2 \cdots \left(\frac{1+z_n x_n}{2}\right)^2}$$

- $\deg(g_z) \leq n$ and g_z is a polynomial.
- $\{g_z\}_{z \in \{\pm 1\}^n}$ is a degree 2n SoS certificate. Q.E.D.

"Smaller" SoS certificate?

- If there exists a deg d SoS cert., coeffs $\leq 2^{\text{poly}(n^d)}$.
 - Proof uses the fact that f is on the hypercube.

• How large is r if there exists a deg d SoS cert.?

Notations and Definitions

• Every vector is a column vector by default.

•
$$v^{\otimes 2} = v \otimes v \in \mathbb{R}^{n^2}, v^{\otimes 2}(i,j) = v_i \cdot v_j$$

•
$$(1, v) = (1, v_1, ..., v_n) \in \mathbb{R}^{n+1}$$

- $(1, x)^{\otimes d}$: all possible monomials with deg $\leq d$ with redundancy.
 - Suppose $x = (x_1, x_2)$ and d = 4.

$$(1,x)^{\otimes d/2} = (1,x)^{\otimes 2} = (1,x_1,x_2,x_1,x_1^2(=1),x_1x_2,x_2,x_2x_1,(x_2^2=1))$$

Notations and Definitions

• A matrix $M \in \mathbb{R}^{n \times n}$ is <u>positive semidefinite</u> (PSD) (or $M \ge 0$) iff M is symmetric and $v^T M v \ge 0$ for all $v \in \mathbb{R}^n$.

• Fact. For all positive semidefinite matrix $A \in \mathbb{R}^{n \times n}$, $\exists B \in \mathbb{R}^{m \times n} \ (m \leq n)$ s.t. $A = B^T B$.

Theorem. f has a deg d SoS cert. iff $\exists A \ge 0$ s.t. $((1,x)^{\otimes d/2})^T A(1,x)^{\otimes d/2} = f$.

• Proof, \Rightarrow part) Let $\{g_i\}$ be a deg d SoS cert.

• Let v_i be a vector s.t. $g_i = v_i^T (1, x)^{\otimes d/2}$. Intuitively, v_i is a coeff. vector of g_i .

•
$$f = \sum_{i} (v_i^T (1, x)^{\otimes d/2})^2 = \sum_{i} (v_i^T (1, x)^{\otimes d/2})^T v_i^T (1, x)^{\otimes d/2}$$

$$= \sum_{i} \left((1, x)^{\otimes d/2} \right)^T v_i v_i^T (1, x)^{\otimes d/2}$$

$$= \left((1, x)^{\otimes d/2} \right)^T \left(\sum_i v_i v_i^T \right) (1, x)^{\otimes d/2}$$

This matrix is PSD.

Theorem.
$$f$$
 has a deg d SoS cert. iff
 $\exists A \ge 0 \text{ s.t. } \left((1, x)^{\otimes d/2} \right)^T A(1, x)^{\otimes d/2} = f.$
• Proof, \leftarrow part) $f = \left((1, x)^{\otimes d/2} \right)^T B^T B(1, x)^{\otimes d/2}$ for some B .

•
$$f = (B(1,x)^{\otimes d/2})^T B(1,x)^{\otimes d/2} = \|B(1,x)^{\otimes d/2}\|_2^2$$

sum of squares of each entry of $B(1, x)^{\otimes d/2}$

- Let g_i be the *i*-th entry of $B(1, x)^{\otimes d/2}$.
- Note $\deg(g_i) \leq d/2$ and $f = \sum_i g_i$ and g_i is polynomial. Q.E.D.

Corollary

- If f has a deg d SoS cert., then \exists a deg d SoS cert. g_1, \dots, g_r where $r \leq (n+1)^{d/2}$.
 - Recall "Let g_i be the *i*-th entry of $B(1, x)^{\otimes d/2}$ " part.

So far...

• If
$$\exists A \ge 0$$
 s.t. $\left((1, x)^{\otimes d/2} \right)^T A(1, x)^{\otimes d/2} = f$,

we can construct a deg d SoS cert. g_1, \dots, g_r w/ $r \leq (n+1)^{d/2}$

• How to find such A?

Understanding
$$((1,x)^{\otimes d/2})^T A(1,x)^{\otimes d/2}$$

- Each element of $(1, x)^{\otimes d/2}$ corresponds to $x^{S} \coloneqq \prod_{i \in S} x_i$ for some set *S*, i.e., $(1, x)^{\otimes d/2}$ can be indexed by monomials.
- Similarly, each row and column of A can be indexed by a set.
- Consider $A_{S,S'}$ which is S-th row and S'-th column of A. It contributes to $\hat{f}(U)$, coeff. of x^U in f where $x^U \equiv x^S \cdot x^{S'}$.

equivalence after the multilinear reduction

Equivalent Statements

• Find
$$A \ge 0$$
 s.t. $\left((1,x)^{\otimes d/2}\right)^T A(1,x)^{\otimes d/2} = f$.

• Find $A \ge 0$ s.t. for all $U \subseteq \{1, ..., n\}$ s.t. $|U| \le d$,

$$\sum_{\substack{\forall S,S':\\x^U \equiv x^{S} \cdot x^{S'}}} A_{S,S'} = \hat{f}(U).$$

Semidefinite Programming (SDP)

• We can efficiently find $A \ge 0$ s.t. $\forall U \subseteq \{1, ..., n\}$ s.t. $|U| \le d$,

$$\sum_{\substack{\forall S,S':\\x^U \equiv x^S \cdot x^{S'}}} A_{S,S'} \in \left[\hat{f}(U) - \epsilon, \hat{f}(U) + \epsilon \right] \text{ for some } \epsilon > 0.$$

• Using SDP, we can efficiently solve the "relaxed" one.

maximize or minimize
$$\sum_{i,j} c_{ij} x_{ij}$$
linear objectivesubject to $\sum_{i,j} a_{ijk} x_{ij} = b_k$, $\forall k$,linear constraints $x_{ij} = x_{ji}$, $\forall i, j$, $\forall i, j$, w additional constraint that
a square symmetric matrix of variables is PSD

Semidefinite Programming (SDP)

- Let A' be the returned matrix. We know f' s.t. $\widehat{f'}(U) = \sum_{\substack{\forall S,S':\\x^U \equiv x^S \cdot x^{S'}}} A'_{S,S'}$ has a deg d SoS cert.
- Claim. $f + \epsilon (n+1)^d$ also has a deg d SoS cert.
 - Proof) Since for any U s.t. $|U| \le d$, $|\hat{f}(U) \hat{f}'(U)| \le \epsilon$ we have $\sum_{U:|U|\le d} |\hat{f}(U) - \hat{f}'(U)| \le \epsilon (n+1)^d$.
 - Claim. For any $h: \{\pm 1\}^n \to \mathbb{R}$ w/ deg $(h) \le d$, we can show $h + \sum_{U:|U| \le d} |\hat{h}(U)|$ has a deg d SoS cert. (proof omitted)
 - $f f' + \epsilon (n + 1)^d$ and f' both have a deg d SoS cert. Q.E.D.

Theorem.

• There is an efficient algorithm that

if the given $f: \{\pm 1\}^n \to \mathbb{R}$ (with $\deg(f) \le d$) has a deg d SoS

cert., then the algorithm outputs a deg d SoS cert. for $f + \epsilon'$.

- Recall $f_G(x) \coloneqq \frac{1}{4} \sum_{(i,j) \in E} (x_i x_j)^2$ is the function over $\{\pm 1\}^{|V|}$.
- Let c' be the (almost) smallest value s.t. the alg. outputs a deg 2 SoS cert. for $c' - f_G(x) + \epsilon'$.
 - The alg. didn't return a deg 2 SoS cert. for $c'' f_G(x) + \epsilon'$ for c'' < c'.
- Our hope is that $\alpha \cdot f_G(x^*) \leq c' (\leq f_G(x^*))$ for some $\alpha \leq 1$.

Theorem.

There is an efficient algorithm that

if the given $f: \{\pm 1\}^n \to \mathbb{R}$ (with $\deg(f) \le d$) has a deg d SoS

cert., then the algorithm outputs a deg d SoS cert. for $f + \epsilon'$.

• Even if *f* does not admit a deg *d* SoS cert., we want some (efficient) "dual object" that we can utilize.

Duality and Sum-of-Squares Algorithm

Geometric Intuition

- What does it mean that \nexists deg d SoS cert. for some \overline{f} ?
- Let $SoS_d \coloneqq \{f: \{\pm 1\}^n \to \mathbb{R} \mid f \text{ has a deg } d \text{ SoS cert.} \}$
- Observe that SoS_d is a convex cone, i.e., closed under convex combination & nonnegative scaling.
- If $\overline{f} \notin SoS_d$, then there should be a separating hyperplane! through the origin

Geometric Intuition

• We can represent a hyperplane by $\mu: \{\pm 1\}^n \to \mathbb{R}$.

• WLOG, $\sum_{x \in \{\pm 1\}^n} \mu(x) = 1.$

- Consider the halfspace H that contains SoS_d but not \overline{f} , i.e., $H = \{h: \{\pm 1\}^n \to \mathbb{R} \mid \sum_{x \in \{\pm 1\}^n} \mu(x)h(x) \ge 0\}.$
- If $\mu(x) \ge 0$ for all x, μ can be seen as a prob. distribution.

For all $f \in SoS_d$, $E_{x \sim \mu}[f(x)] \ge 0$ but $E_{x \sim \mu}[\bar{f}(x)] < 0$. μ serves as a dual object!

Geometric Intuition

• We can represent a hyperplane by $\mu: \{\pm 1\}^n \to \mathbb{R}$.

• WLOG, $\sum_{x \in \{\pm 1\}^n} \mu(x) = 1.$

- Consider the halfspace H that contains SoS_d but not \overline{f} , i.e., $H = \{h: \{\pm 1\}^n \to \mathbb{R} \mid \sum_{x \in \{\pm 1\}^n} \mu(x)h(x) \ge 0\}.$
- What if $\mu(x) < 0$ for some x, i.e., not a prob. dist.? We will see that μ still behaves prob.-like distribution. (pseudo)

(More) Notations and Definitions

- Formal expectation of $f: \{\pm 1\}^n \to \mathbb{R}$ w.r.t. a distribution μ $\tilde{E}_{\mu}[f] = \sum_{x} \mu(x) f(x)$
 - μ is not necessarily a probability distribution! (Therefore, $x \sim \mu$ is not well defined.)

(More) Notations and Definitions

- A deg d pseudo-distribution (over the hypercube) is a function μ (over the hypercube) s.t.
 - $\tilde{E}_{\mu}[1] = 1$, (i.e., the sum of entries of μ is 1) and
 - for every polynomial g of deg(g) $\leq d/2$, $\tilde{E}_{\mu}[g^2] \geq 0$.

Captures the "separating hyperplane condition"

• A <u>deg d pseudo-expectation</u>

is a formal expectation w.r.t. a deg d pseudo-distribution.

Pseudo-distribution as a dual object

- We will see a pseudo-distribution will serve as a dual object.
 - Technical issue: How can we represent a pseudo-distribution?
 - Answer: For all deg d pseudo-dist. μ , there is a deg d pseudo-dist. μ' with deg $(\mu') \leq d$.
 - -> use multilinear reduction

Duality of SoS Cert. and Pseudo-dist.

- Theorem. For every $f: \{\pm 1\}^n \to \mathbb{R}$ and every even $d \in \mathbb{N}$,
 - $f \in SoS_d$ iff every deg d pseudo-dist. μ satisfies $\tilde{E}_{\mu}[f] \ge 0$.
 - Proof, \Rightarrow part) $f = \sum_i g_i$ where $\deg(g_i) \le d/2$. $\tilde{E}_{\mu}[f] = \sum_i \tilde{E}_{\mu}[g^2] \ge 0$.
 - Proof, ⇐ part) Sps *f* ∉ SoS_d. Consider a separating hyperplane μ.
 We show μ is a deg d pseudo-dist. Suffices to show *E*_μ[1] > 0.
 We have *E*_μ[*f*] < 0. Choose large enough L s.t. *E*_μ[*f* + L] ≥ 0.
 Since L · *E*_μ[1] = *E*_μ[L] we have *E*_μ[1] ≥ −*E*_μ[*f*]/L and RHS>0. QE.D.

SoS Algorithm

- Theorem. There is an efficient algorithm that, given f, either outputs a deg d SoS cert. for $f + \epsilon'$ or outputs a pseudo-dist. μ s.t. $\tilde{E}_{\mu}[f] < \epsilon'$.
 - We know there is a pseudo-dist. μ s.t. *Ẽ*_μ[*f*] < 0 if *f* ∉ SoS_d but we don't know how to find it efficiently. Instead, as in finding a SoS cert., we can efficiently compute the "approximate" pseudo-dist. using SDP.

Side note) Equiv. Defn. of Pseudo-dist.

• Let
$$M_{d/2} \coloneqq (1,x)^{\otimes d/2} \left((1,x)^{\otimes d/2} \right)^T$$
.

element-wise pseudo-expectation

- μ is a deg *d* pseudo-dist. iff $\tilde{E}_{\mu}[1] = 1$ and $\tilde{E}_{\mu}[M_{d/2}] \ge 0$.
 - proof) Consider any polynomial $g \ll \deg(g) \le d/2$.

•
$$\tilde{E}_{\mu}[g^2] = \tilde{E}_{\mu}\left[\left(\sum_{S:|S| \le d/2} \hat{g}(S) x^S\right)^2\right] = \tilde{E}_{\mu}\left[\sum_{S,S':|S|,|S'| \le d/2} \hat{g}(S) \hat{g}(S') x^S x^{S'}\right]$$

$$= \sum_{S,S':|S|,|S'| \le d/2} \hat{g}(S) \hat{g}(S') \tilde{E}_{\mu} [x^{S} x^{S'}] = (\hat{g})^{T} M_{d/2}(\hat{g}). \text{ Q.E.D.}$$

changing the order of summation

Max-Cut Algorithm

- Suppose $c' f_G \in SoS_2$ but $c' \epsilon' f_G \notin SoS_2$.
- The sum-of-squares alg. outputs a deg 2 pseudo-dist. μ over the hypercube s.t. $\tilde{E}_{\mu}[c' - \epsilon' - f_G] < \epsilon'$, i.e., $\tilde{E}_{\mu}[f_G] > c' - 2\epsilon'$.
- If μ is an actual prob. dist., we are happy.

• $E_{\mu}[f_G] = \tilde{E}_{\mu}[f_G] > f_G(x^*) - 2\epsilon'$

• If not, "round" a pseudo-dist. into an actual prob. dist. μ' .

• Theorem. For every G and deg 2 pseudo-dist. μ over the hypercube, there exists a prob. dist. μ' over the hypercube s.t.

$$E_{\mu'}[f_G] \ge \alpha \tilde{E}_{\mu}[f_G]$$

where $\alpha = 0.878$... (to be defined more precisely later).

• Corollary 1. Finding μ' efficiently leads to an $(\alpha - 2\epsilon')$ -approx. alg. (or 0.878-approx. alg.)

• Theorem. For every G and deg 2 pseudo-dist. μ over the hypercube, there exists a prob. dist. μ' over the hypercube s.t.

$$E_{\mu'}[f_G] \ge \alpha \tilde{E}_{\mu}[f_G]$$

where $\alpha = 0.878$... (to be defined more precisely later).

- Corollary 2. $f_G(x^*)/\alpha f_G \in SoS_2$.
 - Sps not. Then there is a deg 2 pseudo-dist. μ s.t. $\tilde{E}_{\mu}[f_G(x^*)/\alpha f_G] < 0$.
 - By the above thm, $\exists \mu'$ s.t. $\alpha \tilde{E}_{\mu}[f_G] \leq E_{\mu'}[f_G]$. Contradiction. Q.E.D.

Proof of the Theorem.

• (To be filled out)

Final Remarks CSP, UGC and SoS

2-CSP (Constraint Satisfaction Problems)

- x_1, \ldots, x_n are variables; take values in some finite alphabet Σ .
- $(x_{i_1}, x_{i_2}), A_i$ are *i*-th constraints; $1 \le i \le m$.

The number 2 of 2-CSP comes from here. Constraints consist of at most 2 variables.

- I will call A_i "allowable assignment" of x_{i_1} and x_{i_2} .
- We give an assignment $x' \in \Sigma^n$.

We say *i*-th constraint is satisfied if $(x'_{i_1}, x'_{i_2}) \in A_i$.

• Goal: find an assignment that maximizes #satisfied constraints.

2-CSP (Constraint Satisfaction Problems)

- Max-Cut
 - Variable for each vertex; $\Sigma = \{\pm 1\}$ for each e = (i, j), constraint $= (x_i, x_j), \{(1, -1), (-1, 1)\}.$
- Max-2-Sat
 - Variable for each vertex; $\Sigma = \{T, F\}$; for each constraint, $(x_{i_1}, x_{i_2}), \{(T, F), (F, T), (T, T)\}$
- Max-3-Coloring
 - Variable for each vertex; $\Sigma = \{R, G, B\}$; for each e = (i, j), constraint = (x_i, x_j) , $\{(R, G), (R, B), (G, R), (G, B), (B, R), (B, G)\}$.

Unique 2-CSP

- A constraint $(x_{i_1}, x_{i_2}), A_i$ is <u>unique</u> if for any assignment to one variable (x_{i_1}) , there is exactly one assignment to the other variable (x_{i_2}) that makes the constraint satisfied.
- 2-CSP is called <u>unique</u>, if all constraints are unique.
 - Max-Cut is unique but Max-2-Sat or Max-3-coloring are not unique.
- Unique game (UG) is another name for unique 2-CSP.

(c,s)-CSP

- Given a CSP instance, decide if
 - there is an assignment that satisfies at least $c \cdot m$ constraints
 - for any assignment, #satisfied constraints is at most $s \cdot m$.

- Obs. (1, 1 1/m)-CSP is checking the satisfiability.
- Obs. (1,1-1/m)-UG is polytime solvable.

Unique Game Conjecture (Khot'02)

- For every sufficiently small $\epsilon > 0$, there is a large enough constant k such that
 - $(1 \epsilon, \epsilon)$ -UG is NP-hard where $|\Sigma| = k$.

- Obs. Uniform random assignment satisfies 1/k fraction.
 - This implies $k \gg 1/\epsilon$.

Under UGC,

- for every $\epsilon > 0$, $(\alpha + \epsilon)$ -approx for Max-Cut is NP-hard
 - There are many similar results such as

 $\forall \epsilon > 0$, $(2 - \epsilon)$ -approx for Vertex Cover is NP-hard, ...

It turns out that (by Raghavendra'08)

for all CSP, a "natural" SDP (deg 2 SoS) + "natural" rounding is optimal.

+ And it matches the integrality gap.

Conclusion

- For deg 2 SoS, we know the exact power for CSP.
- deg d SoS for d = 4,6, ...? Nothing known.

• SoS proof technique in other fields?