

# On the Generation of Positivstellensatz Witnesses in Degenerate Cases

Working around geometrical degeneracy in semidefinite  
programming

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# Witnesses of unsatisfiability

To show that  $F$  is satisfiable: exhibit  $\mathcal{M}$  such that  $\mathcal{M} \models F$ .  
But to show that  $F$  is unsatisfiable? *Negativa non sunt probanda.*

Witness conveys **confidence** of proof — opposed to **blind trust** in a system saying “unsat”.

# Linear real inequalities

Farkas' lemma:

$$\begin{cases} L_1(x, y, \dots) \leq C_1 \\ \vdots \\ L_n(x, y, \dots) \leq C_n \end{cases}$$

has no solution iff  $\exists \lambda_1, \dots, \lambda_n \geq 0$  st  $\sum_i \lambda_i L_i$  is the null linear form and  $\sum_i \lambda_i C_i < 0$ , so the combination is  $0 \leq -1$  (or any  $0 \leq C$  where  $C < 0$ ).

Looking for such  $\lambda_i$  = finding a solution to **dual system of (in)equalities**.

# Complex polynomial equalities

Hilbert's Nullstellensatz (on  $\mathbb{C}$ ):

$$\begin{cases} P_1(x, y, \dots) = 0 \\ \vdots \\ P_n(x, y, \dots) = 0 \end{cases}$$

has no solution iff 1 belongs to the ideal  $I$  generated by  $P_1, \dots, P_n$ :  $\exists Q_1, \dots, Q_n$  st  $\sum_i Q_i P_i = 1$ .

Such  $Q_i$  can be computed by dividing 1 by a **Gröbner basis** for  $P_i$  (e.g. Buchberger's algorithm).

# Good witnesses

Usage: convince people (or Coq or whatever) that a system is unsatisfiable by giving them a witness proving that.

An **unsatisfiability witness** for a system of relations should be **easy to check**

- ▶ low algorithm and implementation complexity (checking phase should be easy to understand)
- ▶ ideally, low time and space complexity

In both previous examples, **checking the witness is simple** formal math, **finding it is harder**.

Tackle: **polynomial real inequalities**.

# Hilbert's 17th problem

Proving that  $P < 0$  is unsatisfiable  $\Leftrightarrow$  proving  $P \geq 0$ .

One method: prove that  $P$  is a **sum of squares of polynomials** (SOS).

Not a complete method: some  $P \geq 0$  are not sums of squares of polynomials.

Artin: any  $P \geq 0$  is a **sum of squares of rational functions**.

Thus: any  $P \geq 0$  is  $N/D$  where  $N, D$  sums of squares of polynomials.

Equivalently:  $PD - N = 0, D \neq 0$

# Positivstellensatz

Stengle, 1973

$$\begin{cases} P_1(x, y, \dots) \geq 0 \\ \vdots \\ P_n(x, y, \dots) \geq 0 \end{cases}$$

has no solution iff there exists  $Q_j$  **sum of squares of polynomials** such that  $\sum_j Q_j \tilde{P}_j = -1$ , where the  $\tilde{P}_j$  are the  $2^n$  products of the form  $\prod_i P_i^{\alpha_i}$  where  $\alpha_i \in \{0, 1\}$ .

# The sums-of-squares problem

Given  $P_1, \dots, P_n, R \in \mathbb{Q}[X_1, \dots, X_m]$ , solve

$$\sum_i P_i Q_i = R$$

where the  $Q_i$  are sums of squares of polynomials in  $\mathbb{Q}[X_1, \dots, X_m]$ .



# Reduction to semidefinite programming

$Q \in \mathbb{Q}[X_1, \dots, X_m]$  is a SOS polynomial over monomials  $m_1, \dots, m_l$  iff  $Q = m\hat{Q}m^T$  with  $m$  vector  $m_1, \dots, m_l$  and  $\hat{Q}$  is a **positive semidefinite** (sdp) rational matrix.

Sdp matrix = symmetric matrix with nonnegative eigenvalues, noted  $\hat{Q} \succeq 0$

Thus  $P_i Q_i = R$  iff there exist sdp matrices  $\hat{Q}_i$  st  $\sum_i P_i(m\hat{Q}_i m^T) = R$ .

Equality between polynomials iff equality of coefficients for all monomials. Write this as system of equalities between the coefficients of  $\hat{Q}_i$ .

# Reduction to semidefinite programming

The coefficients of  $\hat{Q}$  satisfy a given system of linear equalities  
 $\Rightarrow$  solve them for a system of generators.

Then find sdp combination of the generators.

= semidefinite programming feasibility problem, solved by  
interior point methods

# Summary so far

(See e.g. Harrison TPHOL 2007)

We have reduced unsatisfiability witness search problems to:

- ▶ defining some monomial basis  $m_1, \dots, m_l$  (no good bounds on the degrees of the monomials needed, in general)
- ▶ looking for a **rational** solution to a pure feasibility semidefinite programming problem  $-F_0 + \sum_i \lambda_i F_i \succeq 0$ .

(Note: general semidefinite programming = optimize a linear form over the solution set.)

How do we solve the semidefinite programming problem?

Numerically, but...



# The spectrahedron

The locus of the  $(\lambda_1, \dots, \lambda_d)$  such that  $-F_0 + \sum_i \lambda_i F_i \succeq 0$  is sometimes called the **spectrahedron**.

Its dimension  $\leq d$  is the dimension of its affine linear span.

- ▶ point: dimension 0
- ▶ segment: dimension 1
- ▶ disc or square: dimension 2
- ▶ cube or spherical ball: dimension 3

Unfortunately, the spectrahedron is not necessarily full dimensional (= is flat).

It is full dimensional iff it has **nonempty interior**.

In many practical cases, it has empty interior.

# Geometrical degeneracy

For problems with an empty interior, numerical solving **fails** to produce a checkable solution.

For the most reliable methods,, converge to an approximate solution  $F$ : a **few very small negative eigenvalues** ( $-10^{-7}$  or so on small examples).

Articles on exact sdp solving and sums-of-squares generally assume **"strict feasibility"**!

# The problem is easy if strictly feasible

Compute  $\tilde{\lambda}$  such that  $-F_0 + \sum_i \tilde{\lambda}_i F_i \succeq 0$  according to interior point numerical solving. Interior point solving tends to “push away” from the boundaries and give large eigenvalues.  $\Rightarrow$

There is a ball around  $\tilde{\lambda}$  where all matrices are sdP.

Method: round  $\tilde{F} = -F_0 + \sum_i \tilde{\lambda}_i F_i$  to a nearby rational matrix  $F = -F_0 + \sum_i \lambda_i F_i$  (round  $\tilde{\lambda}$  to  $\lambda$  is a simple way), check that  $F \succeq 0$  in exact arithmetic (Gaussian reduction).

This is basically Parrilo & Weyl's method.

# Pipedream

We have a problem  $-F_0 + \sum_{i=1}^d \lambda_i F_i \succeq 0$  with a degenerate spectrahedron.

If we knew the linear affine span of the spectrahedron, we could **reparametrize** and obtain a non-degenerate problem  $-F_0 + \sum_{i=1}^{d'} \lambda_i F'_i \succeq 0$  **in a lower dimension**  $d' < d$ .

How can we know it?

# A simple lemma

The nullspace of any matrix in the relative interior of the solution set determines the affine span.

Chicken and egg: get a solution, compute the nullspace, compute the affine span, reparametrize. . . to get a solution

Method: get an **approximate solution**, compute a **reasonable approximate nullspace**, etc.



# Computing the nullspace

Suppose we have an approximate numerical solution  $\tilde{F} = -F_0 + \sum_i \tilde{\lambda}_i F_i$  “almost”  $\succeq 0$  and “close” to an exact rational solution  $F$ .

Then for all vector  $v$  in  $\ker F$ ,  $\tilde{F}.v$  is very small.

Bold assumption:  $\ker F$  has a basis of small integer vectors.  
Then: look for “small”  $v$  such that  $\tilde{F}.v$  is very small.

Do it by **LLL (Lenstra - Lenstra - Lovasz) lattice reduction**.

# Algorithm

Repeat until success or failure:

- ▶ Solve  $\tilde{F} = -F_0 + \sum_{i=1}^d \tilde{\lambda}_i F_i \succeq 0$  numerically.
- ▶ If failed, answer “failure”.
- ▶ Round  $\tilde{\lambda}_i$  to  $\lambda_i \in \mathbb{Q}$ .
- ▶ If  $-F_0 + \sum_i \lambda_i F_i \succeq 0$  exactly, answer “success” and print out the  $\lambda_i$ .
- ▶ Otherwise, compute some short vectors  $v$  such that  $\tilde{F}.v$  is small.
- ▶ Add the constraint that the solution matrix  $F$  should satisfy  $F.v = 0$  to the system, obtain a lower dimension problem.

# On Positivstellensatz proofs

$$\left\{ \begin{array}{l} P_1 = x^3 + xy + 3y^2 + z + 1 \geq 0 \\ P_2 = 5z^3 - 2y^2 + x + 2 \geq 0 \\ P_3 = x^2 + y - z \geq 0 \\ P_4 = -5x^2z^3 - 50xyz^3 - 125y^2z^3 + 2x^2y^2 + 20xy^3 \\ \quad + 50y^4 - 2x^3 - 10x^2y - 25xy^2 - 15z^3 - 4x^2 \\ \quad - 21xy - 47y^2 - 3x - y - 8 \geq 0 \end{array} \right.$$

has no solution, but Mathematica 5 (cylindrical algebraic decomposition) cannot prove it, neither can Redlog and QepCad.

Mathematica 7 can but provides no witness.

Our method quickly finds a witness.

# Proving impossibilities

14 problems from John Harrison, e.g.

$$0 \leq x \wedge 0 \leq y \wedge 0 \leq z \wedge (xyz = 1) \implies x+y+z \leq x^2z+y^2x+z^2y \quad (1)$$

John's sdp reduction does not converge due to degeneracy,  
ours converges.

# Proving nonnegativity

Took examples in the literature on nonnegative polynomials

- ▶ known **not to be sums of squares** of polynomials
- ▶ known to be nonnegative

Compute exact witnesses that they were quotients of sums of squares it at most 7 minutes.

Only one polynomial resisted — large degree, large coefficients, our implementation is too slow.

## Coq proof extract

$P$  nonnegative polynomial because  $P = N/D$ ,  $N$  and  $D$  sums of squares.

**Definition** num:=eval\_SOS num\_decomp.

**Definition** denom:=eval\_SOS denom\_decomp.

**Lemma** non\_critical : forall p q r:Q, r\*q == p → p ≥ 0 → q ≥ 0 → ~ q == 0 → r ≥ 0.

**Lemma** Ident: poly \* denom == num.

**unfold** poly, denom, denom\_decomp, num, num\_decomp.

**simpl** eval\_SOS. **ring**.

**Qed**.

**Lemma** T: ~ denom == 0 → poly ≥ 0.

intros.

apply non\_critical with num denom.

apply Ident. apply pos\_SOS. apply pos\_SOS.

assumption.

**Qed**.



# Open problems

Under which **conditions of precision** does this method converge? How do I set the **“scaling factors”** used for LLL?

Delicate question: there exist sdp problems that have rational solutions, but none in the relative interior. Thus the assumption that “there is a nearby rational solution” is false in general.

Is it possible to obtain such bad problems from a  $\sum_i Q_i P_i = R$  equation ( $Q_i \succeq 0$ )?

# So far

Naive implementation in Sage (Python-based math program).  
Post-processing to Coq proofs.

Scalability issues.

Recent work: generate the nullspace faster (use multiple matrices in LLL).