# Algebraic and Semi-Algebraic Reasoning For Formal Methods

Lecture 4 - Applications of Gröbner Bases and Sum of Squares.

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#### **Operations on Varieties**

- ullet Algebraic Variety V
  - lacktriangle Representation: Gröbner basis of the ideal  $\operatorname{Id}(V)$ .
- Intersection of varieties:
  - $\bullet \ \ V_1 \cap V_2 \mathsf{Groebner}(G_1 \cup G_2)$
  - Why do we need to compute Gröbner basis again?
- Union of varieties:
  - $\bullet \quad V_1 \cup V_2 G_1 \otimes G_2 \text{ or } \langle G_1 \rangle \cap \langle G_2 \rangle.$

#### **Unions of Varieties**

Two ways of computing intersections:

$$\begin{split} \operatorname{Var}(\langle f_1, \dots, f_j \rangle) & \cup \operatorname{Var}(\langle g_1, \dots, g_k \rangle) \\ & = \operatorname{Var}(\langle f_1 g_1, f_1 g_2, \dots, f_j g_k \rangle) \\ & = \operatorname{Var}(\langle f_1, \dots, f_j \rangle \cap \langle g_1, \dots, g_k \rangle) \end{split}$$

- How do we compute ideal intersections?
- Which one is better?

#### **Ideal Intersection**

**Trick** Let t be a fresh variable.

$$\begin{split} \langle f_1, \dots, f_j \rangle \cap \langle g_1, \dots, g_k \rangle &= \\ \langle tf_1, \dots, tf_j, (1-t)g_1, \dots, (1-t)g_k \rangle \cap K[\vec{x}] \end{split}$$

- Prove that this computes ideal intersection
- Eliminate the variable t.
  - We will see how to do so soon.

#### **Ideal Products**

Let 
$$p\in \langle f_1,\dots,f_j\rangle\cap \langle g_1,\dots,g_k\rangle$$
 then  $p\in \langle f_1g_1,f_1g_2,\dots,f_jg_k\rangle$ ?

- Not necessarily!
- However,  $p^2 \in \langle f_1 g_1, f_1 g_2, \dots, f_j g_k \rangle$ ?.

If 
$$p \in \langle f_1g_1, f_1g_2, \dots, f_jg_k \rangle$$
, is  $p \in \langle f_1, \dots, f_j \rangle \cap \langle g_1, \dots, g_k \rangle$ ?

#### **Inclusion Checking**

- Algebraic Varieties:  $V_1, V_2$ .
- Check if  $V_1 \subseteq V_2$ .
  - $\bullet$  Let  $\langle G_1 \rangle, \langle G_2 \rangle$  be the Gröbner bases.
- If  $V_1 \subseteq V_2$  then  $\langle G_2 \rangle \subseteq \langle G_1 \rangle$ .
- Each gen. in  $G_2$  reduces to 0 under reduction by  $G_1$ ?

#### **Image Computation**

- Image computation:
  - $\bullet \ \ \text{Assertion} \ \varphi: g_1(\vec{x}) = 0 \ \land \ \cdots \ \land \ g_m(\vec{x}) = 0 \\$
  - $\qquad \text{Transition relation } \rho: \ p_1(\vec{x},\vec{x}') = 0 \ \land \ \cdots \ p_m(\vec{x},\vec{x}') = 0.$
  - ${\bf Post\text{-}Condition:}\ (\exists\ \vec{x}_0)\ \varphi[\vec{x}_0]\land\ \rho[\vec{x}_0,\vec{x}]$

Let 
$$I:\langle p_1,\dots,p_m\rangle$$
 be an ideal in  $K[x_1,\dots,x_n,y_1,\dots,y_m].$ 

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  - $\blacksquare$  Eg., lexicographic ordering:  $x_1 > \cdots > x_n > y_1 > \cdots > y_m$

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  - $\bullet \ \widehat{G} = G \cap K[y_1, \dots, y_m]$

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- Take all polynomials involving  $y_1, \dots, y_m$ :
  - $\bullet \ \widehat{G} = G \cap K[y_1, \dots, y_m]$
- $\bullet \quad {\rm Claim} \colon \, I \cap K[y_1, \ldots, y_m] = \langle \widehat{G} \rangle.$

#### **Demonstration**

Demo of using abstract interpretation to calculate polynomial invariants.

Jupyter notebook!

## Semi-Algebraic Reasoning

## Lagrangian Reasoning for Inequalities

$$\begin{array}{ccccc} 2x-3y+4z & \geq & 5 & \leftarrow e_1 \\ 3x-2y+0z & \geq & 7 & \leftarrow e_2 \\ & & z & \geq & 3 & \leftarrow e_3 \\ \hline & & (\Rightarrow) \\ x-y+z & \geq & 3 \\ \\ (x-y+z-3) & = \frac{1}{5}(e_1+e_2+e_3) \end{array}$$

## Lagrangian Reasoning (Continued)

$$\frac{e \ge 0, \ \lambda \ge 0}{\lambda e \ge 0}$$

$$\frac{e_1 \ge 0, \ e_2 \ge 0}{e_1 + e_2 \ge 0}$$

$$1 \ge 0$$

#### **Conic Combination**

Consider linear inequalities

$$e_1 \geq 0, \dots, e_m \geq 0$$

Conic combination:

$$\lambda_0 + \lambda_1 e_1 + \dots + \lambda_m e_m \leq 0$$

wherein  $\lambda_i \geq 0$ .

#### Farkas' Lemma

$$\varphi: e_1 \geq 0 \land e_2 \geq 0 \cdots \land e_m \geq 0$$

- $\varphi$  is unsatisfiable iff  $-1 \ge 0$  lies in conic combination.
- $\bullet$  If  $\varphi$  is satisfiable:  $\varphi \models e \geq 0$  iff we can  $e = \sum_{i=1}^m \lambda_i e_i + \lambda_0$ 
  - $\bullet \quad \lambda_0, \dots, \lambda_m \ge 0.$
- Foundations of linear programming and duality theory.
  - Reference: V. Chvatal's amazing book on Linear Programming.

#### Farkas' Lemma in Formal Methods

- Vast literature on using Farkas' Lemma for
  - Invariant Synthesis: Colon + Sank. + Sipma' CAV 2003;
    Gulwani et al., Tiwari et al.,...
  - Ranking Function Synthesis: Colon + Sipma, Podelski + Rybalchenko, Bradley + Manna, Cook + Rybalchenko + Podelski, ...
  - Cost analysis of programs
  - Analysis of probabilistic programs
  - Proof production in linear arithmetic SMT solver: [Reynolds+Tinelli]

## **Beyond Farkas Lemma**

Proving entailment with polynomials:

$$p_1 \geq 0, \cdots, p_m \geq 0 \ \models \ p \geq 0$$

- $\bullet \quad p_1, \dots, p_m \in \mathbb{R}[x_1, \dots, x_n].$
- Entailment over  $\mathbb{R}^n$ .

Positivstellensatz:

$$p = \sigma_0 + \sigma_1 p_1 + \dots + \sigma_m p_m$$

where  $\sigma_i$  are positive polynomials.

#### **Polynomial Positivity Checking**

- Check if a polynomial  $p \in \mathbb{R}[x_1, \dots, x_n]$  is non-negative everywhere.

$$\forall \ x_1,\ldots,x_n \in \mathbb{R}^n, \ p(x_1,\ldots,x_n) \geq 0$$

- Well known to be NP-hard.
  - Positive Definite: p > 0 for all  $\vec{x} \neq 0$ .
  - Positive Semi-Definite:  $p \ge 0$  for all  $\vec{x}$ .

## Semi-Algebraic Entailment Checking

Given  $p_1,\ldots,p_m,p\in\mathbb{R}[x_1,\ldots,x_n]$ , check entailment:

$$p_1 \geq 0 \ \wedge \ \cdots \ \wedge p_m \geq 0 \ \models \ p \geq 0 \,.$$

Adapt Cylindrical Algebraic Decomposition.

## Cylindrical Algebraic Decomposition (CAD)

Given polynomials  $p_1,\ldots,p_m$  in  $\mathbb{R}[x_1,\ldots,x_n]$ ,

- We decompose  $\mathbb{R}^n$  into finitely many disjoint cells.
- Each cell is semi-algebraic.
- Each cell is "sign invariant".
- The decomposition is *cylindrical*.

#### **Cylindrical Decomposition**

• Decompose  $x_n$  into finitely many points and intervals.

$$\mathbb{R}=(-\infty,a_1)\cup[a_1,a_1]\cup(a_1,a_2)\cup[a_2,a_2]\cup\cdots$$

For each point/interval, we recursively associate a "stack of regions' involving  $x_1,\dots,x_{n-1}.$ 

Cf. Manuel Kauers, How to use a Cylindrical Algebraic Decomposition.

## **CAD** Figure

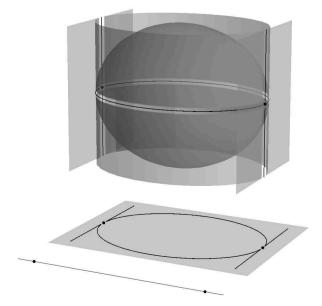


FIGURE 2 cylindrical algebraic decomposition of the unit ball

### Cylindrical Algebraic Decomposition: Complexity

- CAD is a very powerful tool for working with semi-algebraic sets.
- However, its complexity is double exponential in number of variables.
  - The full CAD algorithm is not necessary to check if  $\exists \vec{x}, p(\vec{x}) < 0.$

## **Sum Of Squares Techniques**

## Sum of Squares (SOS)

A polynomial p is sum of squares (SOS) iff

$$p = \sigma_1^2 + \dots + \sigma_k^2$$

for some  $k \geq 0$ .

$$\quad \bullet \quad \sigma_1, \dots, \sigma_k \in \mathbb{R}[x_1, \dots, x_n].$$

### Positive Polynomials vs. Sum-Of-Squares

If p is SOS then p is a positive semi-definite.

- Is the converse true?
  - Theorem # 1 Any univariate polynomial is positive semi-definite iff it is SOS.
- Theorem # 2 Any quadratic polynomial is positive semi-definite iff it is SOS.

TODO: Prove these in lecture.

There exists a polynomial that is positive semidefinite but cannot be written as a sum of squares.

#### Motzkin Polynomial:

$$p = x^4y^2 + x^2y^4 + 1 - 3x^2y^2 \succeq 0$$

- Prove that *p* is positive semi-definite.
- ullet Prove that p cannot be expressed as SOS.

#### **Quadratic Forms and Sum of Squares**

Quadratic polynomial  $p(x_1, \dots, x_n)$  can be written:

$$\begin{pmatrix} 1 \\ x_1 \\ x_2 \\ \dots \\ x_n \end{pmatrix}^\top \begin{pmatrix} Q_{11} & Q_{12} & \cdots & Q_{1,n+1} \\ Q_{21} & Q_{22} & \cdots & Q_{2,n+1} \\ \vdots & & \ddots & \vdots \\ Q_{n+1,1} & Q_{n+1,2} & \cdots & Q_{n+1,n+1} \end{pmatrix} \begin{pmatrix} 1 \\ x_1 \\ x_2 \\ \dots \\ x_n \end{pmatrix}$$

#### SOS and PSD for Quadratic Forms

A quadratic form  $p(\vec{x}) = \vec{x}^\top Q \vec{x}$  is positive semidefinite iff all eigenvalues of Q are non-negative.

**Proof:** Suppose  $Q\vec{v}=\lambda\vec{v}$ ,  $\lambda$  must be real and furthermore,  $\vec{v}^{\top}Q\vec{v}=\lambda\vec{v}^{\top}\vec{v}$ .

- $(\Rightarrow) \text{ Let } p \text{ be a positive semi-definite polynomial, but } Q \text{ have a negative eigenvalue } \lambda < 0. \text{ Then } p(\vec{v}) = \lambda \vec{v}^\top \vec{v} < 0. \text{ This is a contradiction.}$
- ( $\Leftarrow$ ) Suppose all eigen values of Q are non-negative. Since Q is a symmetric matrix, we can write its spectral decomposition:  $Q = \sum_{j=1}^n \lambda_j \vec{v}_j \vec{v}_j^{\mathsf{T}}$ , wherein  $\lambda_j \geq 0$  are the eigenvalues. Therefore,  $p = \vec{x}^{\mathsf{T}} Q \vec{x}$  can be written as

$$p = \sum_{j=1}^{n} \lambda_j \vec{x}^t \vec{v}_j \vec{v}_j^{\top} \vec{x} = \sum_{j=1}^{n} (\sqrt{\lambda_j} \vec{v}_j^{\top} \vec{x})^2$$

#### Hilbert's Seventeenth Problem

**Hilbert's Seventeenth Problem:** Can any positive semi-definite polynomial be written as a sum of squares of rational functions?

$$p = \sum_{j=1}^k \frac{\sigma_j^2}{\xi_j^2}$$

Artin and Schreier'1927: Theory of real-closed fields.

### Why SOS?

- Checking if a polynomial is SOS can be made efficient.
  - Reduction to semi-definite programming (convex optimization).
- Positivstellensatz using Sum of Squares.
  - Lasserre Hierarchy.
  - Next lecture.

### **Checking SOS**

Input:  $p \in \mathbb{R}[x_1, \dots, x_n]$ .

**Output:** Is 
$$p=\sigma_1^2+\cdots+\sigma_k^2$$
 for  $\sigma_1,\ldots,\sigma_k\in\mathbb{R}[x_1,\ldots,x_n]$ ?

Idea: quadratic forms but lift to a higher dimensional space.

- Originally proposed by N. Shor, 1987 (In Russian).
- Rediscovered by Lasserre'2001 and Parrilo'2003.
  - Global Optimization with Polynomials and the Problem of Moments, Jean B. Lasserre, SIAM J. Opt., 2001.
  - Semidefinite programming relaxations for semialgebraic problems, Pablo Parrilo, Math. Prog. Ser. B, 2003.

#### **Checking Sum of Squares: Idea**

Idea Write a non-quadratic polynomial as a quadratic form.

Example 
$$x^4y^2 - 2x^2y^2 + 2y^2 - 2xy + x^2 + 9$$

Let 
$$\mu(x,y) = \begin{pmatrix} x^2y \\ xy \\ x \\ y \\ 1 \end{pmatrix}$$
, Write  $p = \mu^\top Q \mu$ .

## **Example** (Continued)

$$p = x^4y^2 - 2x^2y^2 + 2y^2 - 2xy + x^2 + 9$$

	$x^2y$	xy	$\boldsymbol{x}$	y	1
$x^2y$	1	0	0	-1	0
xy	0	0	0	0	0
x	0	0	1	-1	0
y	-1	0	-1	2	0
1	0	0	0	0	9

**Problem:** Q is not unique.

## **Example: Non-Uniqueness**

$$p = x^4y^2 - 2x^2y^2 + 2y^2 - 2xy + x^2 + 9$$

	$x^2y$	xy	x	y	1
$x^2y$	1	0	0	0	0
xy	0	-2	0	0	0
x	0	0	1	-1	0
y	0	0	-1	2	0
1	0	0	0	0	9

 ${\cal Q}$  is not a psd matrix.

#### Basic Idea.

- $\bullet$  Fix a vector of monomials  $\mu(x_1,\dots,x_n).$
- lacktriangle Try to write polynomial p as
  - $p = \mu^\top Q \mu$
  - ullet Q is a positive semidefinite matrix.
- However, there are infinitely many ways of doing so.
  - We need to discover one way to do it!

#### **Next Session**

- How to check if a polynomial is SOS?
  - Semi-Definite Programming.
- Positivstellensatz.