

# Graph structure in polynomial systems: chordal networks

Pablo A. Parrilo

Laboratory for Information and Decision Systems  
Electrical Engineering and Computer Science  
Massachusetts Institute of Technology



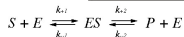
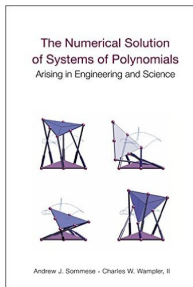
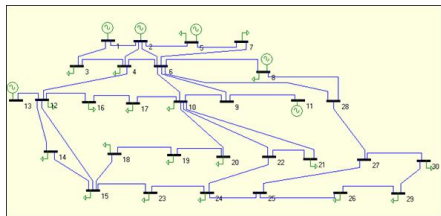
Based on joint work  
with **Diego Cifuentes** (MIT)

SIAM Annual Meeting - July 2016

# Background: structured polynomial systems

Many application domains require the solution of large-scale systems of polynomial equations.

Among others: robotics, power systems, chemical engineering, cryptography, etc.



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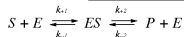
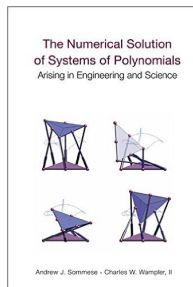
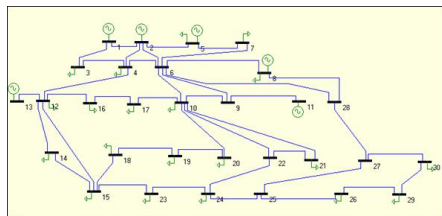
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Today: **MS111/MS126** - Structured Polynomial Equations and Applications

## Polynomial systems and graphs

A polynomial system defined by  $m$  equations in  $n$  variables:

$$f_i(x_0, \dots, x_{n-1}) = 0, \quad i = 1, \dots, m$$

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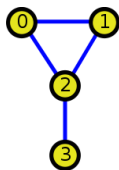
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Example:

$$I = \langle x_0^2 x_1 x_2 + 2x_1 + 1, \quad x_1^2 + x_2, \quad x_1 + x_2, \quad x_2 x_3 \rangle$$



# Questions

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- Can the graph structure help *solve* this system?
- For instance, to optimize, or to compute Groebner bases?
- Or, perhaps we can do something *better*?
- Preserve graph (sparsity) structure?
- Complexity aspects?



# (Hyper)Graphical modelling

Pervasive idea in many areas, in particular: numerical linear algebra, graphical models, constraint satisfaction, database theory, ...

Key notions: **chordality** and **treewidth**.

Many names: Arnborg, Beeri/Fagin/Maier/Yannakakis, Blair/Peyton, Bodlaender, Courcelle, Dechter, Freuder, Lauritzen/Spiegelhalter, Pearl, Robertson/Seymour, ...

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Reasonably well-known in discrete (0/1) optimization, what happens in the continuous side?

(e.g., Waki et al., Lasserre, Bienstock, Vandenberghe, Lavaei, etc)

# Chordality

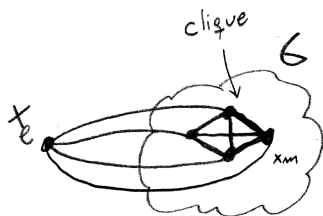
Let  $G$  be a graph with vertices  $x_0, \dots, x_{n-1}$ .  
A vertex ordering

$$x_0 > x_1 > \dots > x_{n-1}$$

is a **perfect elimination ordering** if for all  $l$ ,  
the set

$$X_l := \{x_l\} \cup \{x_m : x_m \text{ is adjacent to } x_l, x_l > x_m\}$$

is such that the restriction  $G|_{X_l}$  is a clique.



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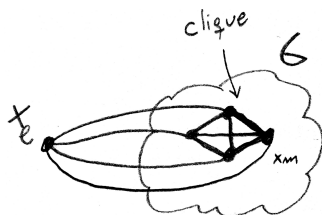
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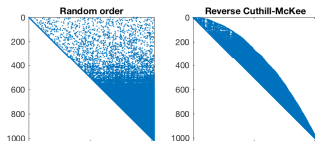
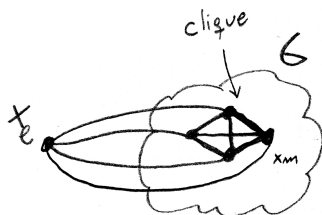
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A graph is **chordal** if it has a perfect elimination ordering.

(Equivalently, in numerical linear algebra:  
Cholesky factorization has no “fill-in”)



## Chordality, treewidth, and a meta-theorem

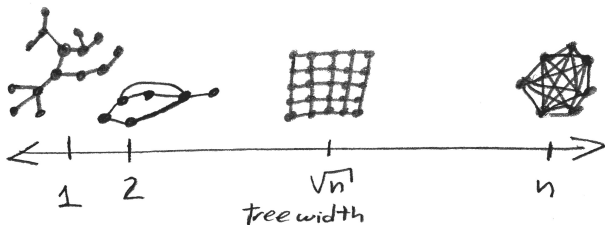
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Informally, treewidth quantitatively measures how “tree-like” a graph is.



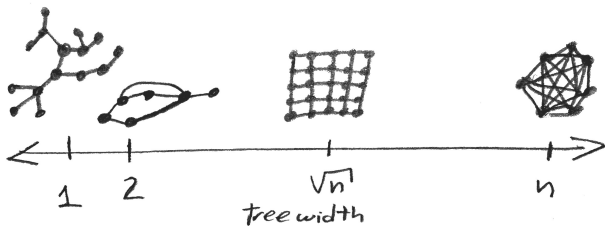


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Meta-theorem:

NP-complete problems are “easy” on graphs of small treewidth.

## Bad news? (I)

Recall the *subset sum* problem, with data  $A = \{a_1, \dots, a_n\} \subset \mathbb{Z}$ .  
Is there a subset of  $A$  that adds up to 0?

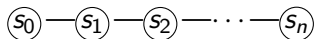
Letting  $s_i$  be the partial sums, we can write a polynomial system:

$$0 = s_0$$

$$0 = (s_i - s_{i-1})(s_i - s_{i-1} - a_i)$$

$$0 = s_n$$

The graph associated with these equations is a path (treewidth=1)



But, subset sum is NP-complete... :(

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Ex: Consider

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**Q:** Are there **alternative descriptions** that “play nicely” with graphical structure?

# How to resolve this (apparent) contradiction?

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Underlying hero/culprit: **dynamic programming** (DP), and more refined cousins (nonserial DP, belief propagation, etc).



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Underlying hero/culprit: **dynamic programming** (DP), and more refined cousins (nonserial DP, belief propagation, etc).

Key: “nice” graphical structure allows DP to work *in principle*. But, we also need to control the *complexity* of the objects DP is propagating. Without this, we’re doomed!

[Ubiquitous theme: “complicated” value functions in optimal control, “message complexity” in statistical inference, ...]

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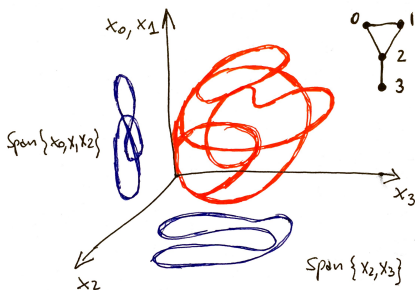
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Require the **projections** onto the  
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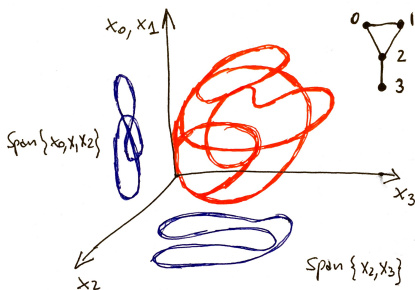
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- For discrete domains (e.g., 0/1 problems), always satisfied.
- Holds in other cases, e.g., low-rank matrices (determinantal varieties).

# Two approaches

- Chordal elimination and Groebner bases (arXiv:1411:1745)
  - New *chordal elimination* algorithm, to exploit graphical structure
  - Conditions under which chordal elimination succeeds
  - For a certain class, complexity is *linear* in number of variables! (exponential in treewidth)
  - Implementation and experimental results
- *Chordal networks* (arXiv:1604.02618)
  - New representation/decomposition for polynomial systems
  - Efficient algorithms to compute them. Can use them for root counting, dimension, radical ideal membership, etc.
  - Links to BDDs (binary decision diagrams) and extensions

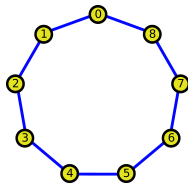
## Example 1: Coloring a cycle

Let  $C_n = (V, E)$  be the cycle graph and consider the ideal  $I$  given by the equations

$$x_i^3 - 1 = 0, \quad i \in V$$

$$x_i^2 + x_i x_j + x_j^2 = 0, \quad ij \in E$$

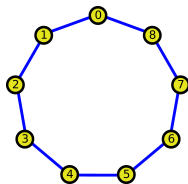
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However, a Gröbner basis is not so simple: one of its 13 elements is

$$\begin{aligned}&x_0 x_2 x_4 x_6 + x_0 x_2 x_4 x_7 + x_0 x_2 x_4 x_8 + x_0 x_2 x_5 x_6 + x_0 x_2 x_5 x_7 + x_0 x_2 x_5 x_8 + x_0 x_2 x_6 x_8 + x_0 x_2 x_7 x_8 + x_0 x_2 x_8^2 + x_0 x_3 x_4 x_6 + x_0 x_3 x_4 x_7 \\&+ x_0 x_3 x_4 x_8 + x_0 x_3 x_5 x_6 + x_0 x_3 x_5 x_7 + x_0 x_3 x_5 x_8 + x_0 x_3 x_6 x_8 + x_0 x_3 x_7 x_8 + x_0 x_3 x_8^2 + x_0 x_4 x_6 x_8 + x_0 x_4 x_7 x_8 + x_0 x_4 x_8^2 + x_0 x_5 x_6 x_8 \\&+ x_0 x_5 x_7 x_8 + x_0 x_5 x_8^2 + x_0 x_6 x_8^2 + x_0 x_7 x_8^2 + x_0 + x_1 x_2 x_4 x_6 + x_1 x_2 x_4 x_7 + x_1 x_2 x_4 x_8 + x_1 x_2 x_5 x_6 + x_1 x_2 x_5 x_7 + x_1 x_2 x_5 x_8 \\&+ x_1 x_2 x_6 x_8 + x_1 x_2 x_7 x_8 + x_1 x_2 x_8^2 + x_1 x_3 x_4 x_6 + x_1 x_3 x_4 x_7 + x_1 x_3 x_4 x_8 + x_1 x_3 x_5 x_6 + x_1 x_3 x_5 x_7 + x_1 x_3 x_5 x_8 + x_1 x_3 x_6 x_8 + x_1 x_3 x_7 x_8 \\&+ x_1 x_3 x_8^2 + x_1 x_4 x_6 x_8 + x_1 x_4 x_7 x_8 + x_1 x_4 x_8^2 + x_1 x_5 x_6 x_8 + x_1 x_5 x_7 x_8 + x_1 x_5 x_8^2 + x_1 x_6 x_8^2 + x_1 x_7 x_8^2 + x_1 + x_2 x_4 x_6 x_8 + x_2 x_4 x_7 x_8 \\&+ x_2 x_4 x_8^2 + x_2 x_5 x_6 x_8 + x_2 x_5 x_7 x_8 + x_2 x_5 x_8^2 + x_2 x_6 x_8^2 + x_2 x_7 x_8^2 + x_2 + x_3 x_4 x_6 x_8 + x_3 x_4 x_7 x_8 + x_3 x_4 x_8^2 + x_3 x_5 x_6 x_8 + x_3 x_5 x_7 x_8 \\&+ x_3 x_5 x_8^2 + x_3 x_6 x_8^2 + x_3 x_7 x_8^2 + x_3 + x_4 x_6 x_8^2 + x_4 x_7 x_8^2 + x_4 + x_5 x_6 x_8^2 + x_5 x_7 x_8^2 + x_5 + x_6 + x_7 + x_8\end{aligned}$$



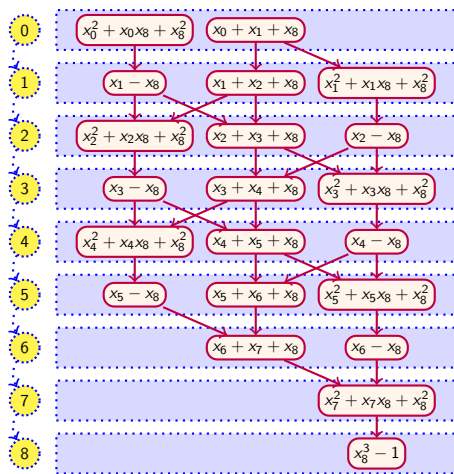
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There is a nicer representation, that respects its graphical structure. The solution set can be *decomposed* into *triangular* sets:

$$\mathcal{V}(I) = \bigcup_T \mathcal{V}(T)$$

where the union is over all *maximal directed paths* in the figure.

The number of triangular sets is 21, which is the 8-th Fibonacci number.



# Chordal networks

A new representation of structured polynomial systems!

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  - “Enlarged” elimination tree, with polynomial sets as nodes.
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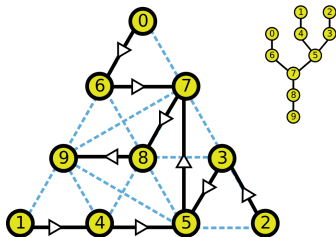
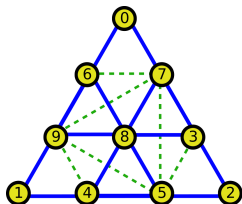
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- What are they good for?
  - Can be effectively used to solve feasibility, counting, dimension, elimination, radical membership, . . .
  - **Linear time** algorithms (exponential in treewidth)
  - Implementation and experimental results.

# Elimination tree of a chordal graph

The **elimination tree** of a graph  $G$  is the following *directed spanning tree*:

For each  $\ell$  there is an arc from  $x_\ell$  towards the largest  $x_p$  that is adjacent to  $x_\ell$  and  $p > \ell$ .

Note that the elimination tree is rooted at  $x_{n-1}$ .



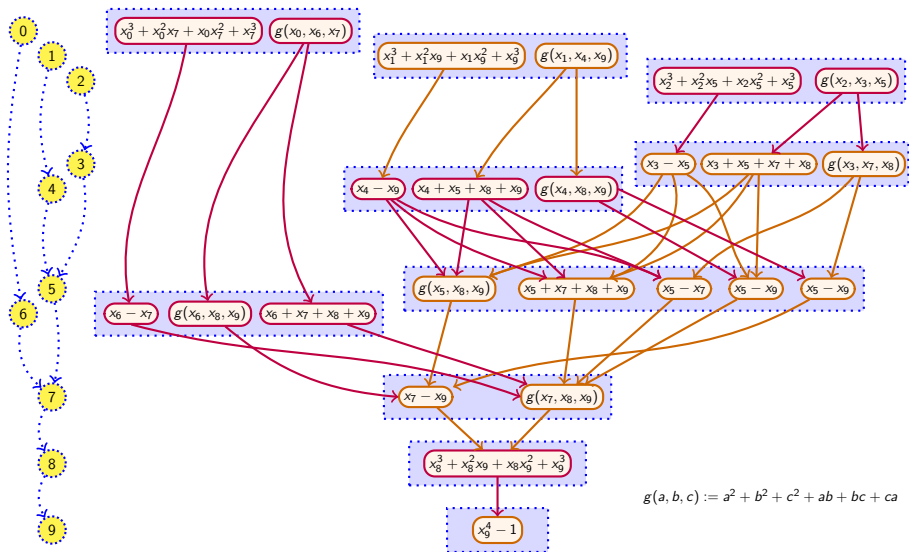
## Chordal networks (definition)

A  **$G$ -chordal network** is a directed graph  $\mathcal{N}$ , whose nodes are polynomial sets in  $\mathbb{K}[X]$ , such that:

- each node  $F$  is given a  $\text{rank}(F) \in \{0, \dots, n-1\}$ , s.t.  $F \subset \mathbb{K}[X_{\text{rank}(F)}]$ .
- for any arc  $(F_\ell, F_p)$  we have that  $x_p$  is the parent of  $x_\ell$  in the elimination tree of  $G$ , where  $\ell = \text{rank}(F_\ell)$ ,  $p = \text{rank}(F_p)$ .

A chordal network is **triangular** if each node consists of a single polynomial  $f$ , and either  $f = 0$  or its largest variable is  $x_{\text{rank}(f)}$ .

# Chordal networks (Example)

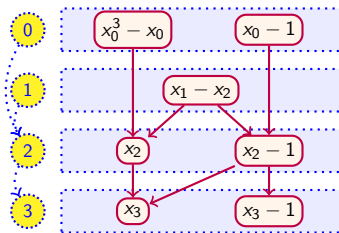


$$g(a, b, c) := a^2 + b^2 + c^2 + ab + bc + ca$$

## Computing chordal networks (Example)

$$I = \langle x_2 - x_3, x_1 - x_2, x_1^2 - x_1, x_0 x_2 - x_2, x_0^3 - x_0 \rangle$$

The output of the algorithm will be

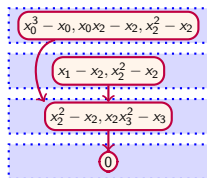


This represents the decomposition of  $I$  into the triangular sets

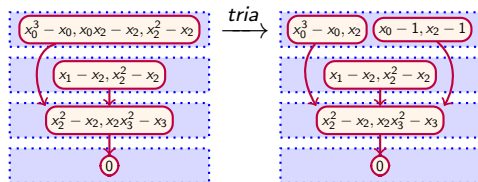
$$\begin{aligned} & (x_3, x_2, x_1 - x_2, x_0^3 - x_0), \\ & (x_3, x_2 - 1, x_1 - x_2, x_0 - 1), \\ & (x_3 - 1, x_2 - 1, x_1 - x_2, x_0 - 1). \end{aligned}$$



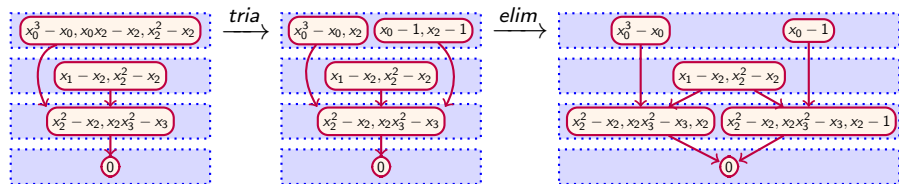
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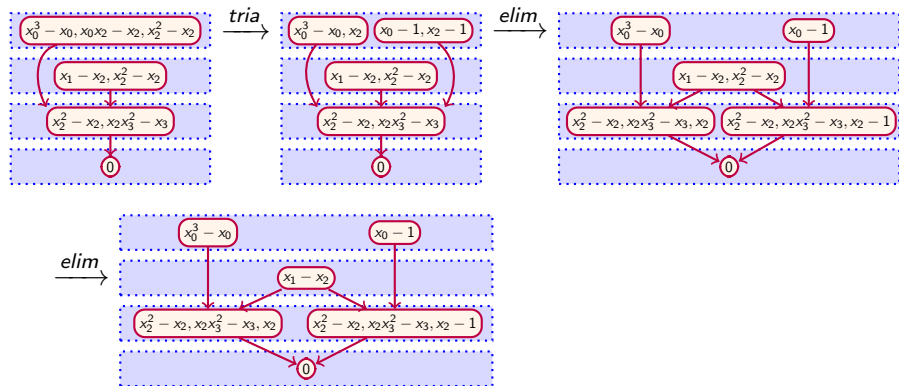
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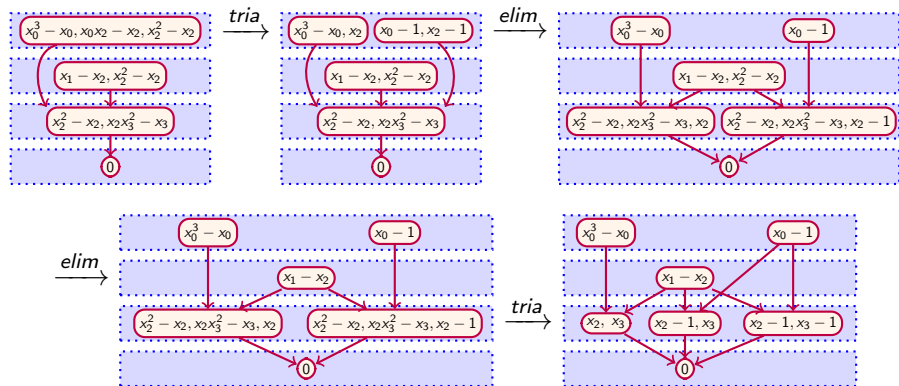
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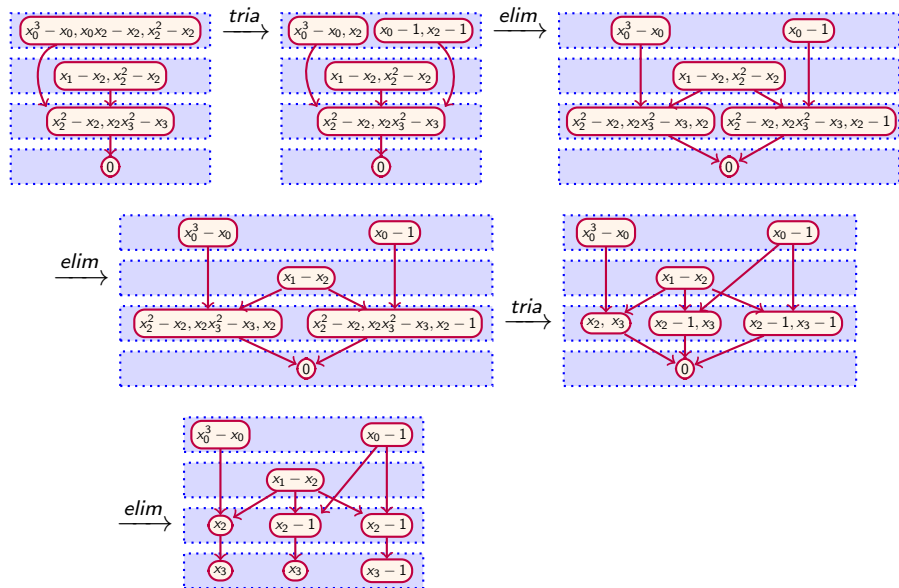
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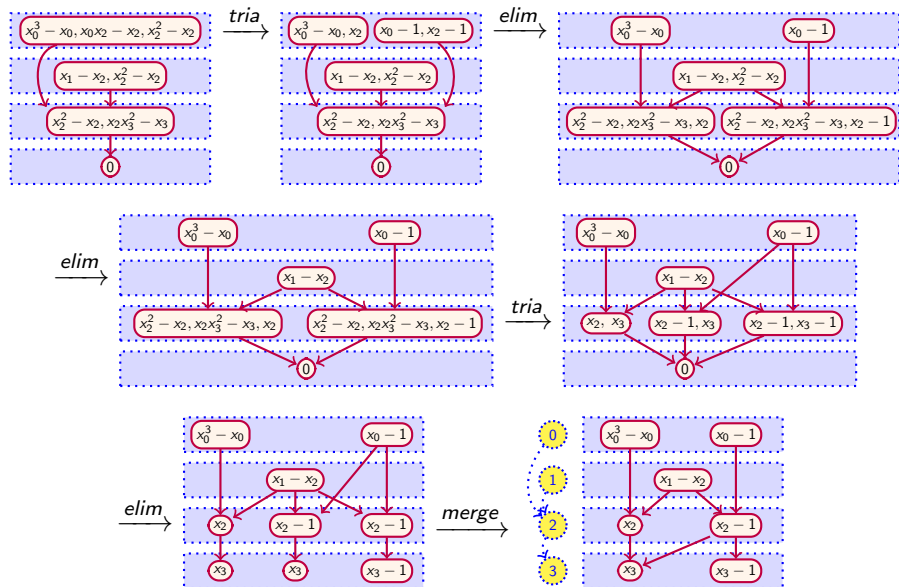
# Computing chordal networks (Example)



# Computing chordal networks (Example)



# Computing chordal networks (Example)



# Chordal networks in computational algebra

Given a triangular chordal network  $\mathcal{N}$  of a polynomial system, the following problems can be solved in **linear** time:

- Compute the cardinality of  $\mathcal{V}(I)$ .
- Compute the dimension of  $\mathcal{V}(I)$
- Describe the top dimensional component of  $\mathcal{V}(I)$ .

We also developed efficient algorithms to

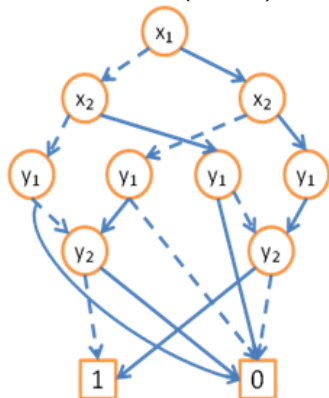
- Solve the radical ideal membership problem ( $h \in \sqrt{I}$ ?)
- Compute the equidimensional components of the variety.



## Links to BDDs

Very interesting connections with *binary decision diagrams* (BDDs).

- A clever representation of Boolean functions/sets, usually much more compact than naive alternatives
- Enabler of very significant practical advances in (discrete) formal verification and model checking
- “One of the only really fundamental data structures that came out in the last twenty-five years” (D. Knuth)



For the special case of *monomial ideals*, chordal networks are equivalent to (reduced, ordered) BDDs. But in general, more powerful!

# Implementation and examples

Implemented in Sage, using Singular and PolyBoRi (for  $\mathbb{F}_2$ ).

- Graph colorings (counting  $q$ -colorings)
- Cryptography (“baby” AES, Cid *et al.*)
- Sensor Network localization
- Discretization of polynomial equations
- Reachability in vector addition systems
- Algebraic statistics

# I - Vector addition systems

Given a set of vectors  $\mathcal{B} \subset \mathbb{Z}^n$ , construct a graph with vertex set  $\mathbb{N}^n$  in which  $u, v \in \mathbb{N}^n$  are adjacent if  $u - v \in \pm\mathcal{B}$ .

**Ex:** Determine whether  $f_n \in I_n$ , where

$$f_n := x_0 x_1^2 x_2^3 \cdots x_{n-1}^n - x_0^n x_1^{n-1} \cdots x_{n-1},$$
$$I_n := \{x_i x_{i+3} - x_{i+1} x_{i+2} : 0 \leq i < n\},$$

and where the indices are taken modulo  $n$ .

We compare our radical membership test with Singular (Gröbner bases) and Epsilon (triangular decompositions).

$n$	5	10	15	20	25	30	35	40	45	50	55
ChordalNet	0.7	3.0	8.5	14.3	21.8	29.8	37.7	48.2	62.3	70.6	84.8
Singular	0.0	0.0	0.2	17.9	1036.2	-	-	-	-	-	-
Epsilon	0.1	0.2	0.4	2.0	54.4	160.1	5141.9	17510.1	-	-	-

## II - Algebraic statistics (Evans et al.)

Consider the binomial ideal  $I^{n,n_2}$  that models a 2D dimensional generalization of the birth-death Markov process. We fix  $n_2 = 1$ .

We can compute all irreducible components of the ideal faster than specialized packages (e.g., Macaulay2's "Binomials")

$n$	1	2	3	4	5	6	7
#components	3	11	40	139	466	1528	4953
time							
ChordalNet	0:00:00	0:00:01	0:00:04	0:00:13	0:02:01	0:37:35	12:22:19
Binomials	0:00:00	0:00:00	0:00:01	0:00:12	0:03:00	4:15:36	-

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Our methods are particularly efficient for computing the **highest dimensional** components.

$n$	Highest 5 dimensions					Highest 7 dimensions			
	20	40	60	80	100	10	20	30	40
#comps	404	684	964	1244	1524	2442	5372	8702	12432
time	0:01:07	0:04:54	0:15:12	0:41:52	1:34:05	0:05:02	0:41:41	3:03:29	9:53:09

# Summary

- (Hyper)graphical structure *may* simplify optimization/solving
- Under assumptions (treewidth + algebraic structure), tractable!
- New data structures: **chordal networks**
- Yields practical, competitive, implementable algorithms
- Ongoing and future work: other polynomial solving approaches (e.g., homotopies, full numerical algebraic geometry...)

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If you want to know more:

- D. Cifuentes, P.A. Parrilo, Exploiting chordal structure in polynomial ideals: a Groebner basis approach. *SIAM J. of Discrete Mathematics*, to appear. [arXiv:1411.1745](https://arxiv.org/abs/1411.1745).
- D. Cifuentes, P.A. Parrilo, An efficient tree decomposition method for permanents and mixed discriminants, *Linear Algebra and Appl.*, 493:45–81, 2016. [arXiv:1507.03046](https://arxiv.org/abs/1507.03046).
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**Thanks for your attention!**

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**Thanks for your attention!**

(and please come to MS111/MS126!)