

Notes by J.H.Davenport

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# Chapter 1

## 16 August

### 1.1 Le and Safey El Din

Many examples, e.g. [MBD<sup>+</sup>18, LMP21]. Classically CAD, but doubly exponential in  $n + t$ .

Can reduce to parametric problem in one variable, but again doubly exponential in  $t = \#$ parameters.

Wnt border polynomials/discriminant varieties. Skipping the boundaries gives us singly-exponential complexity.

We assume  $f$  generates a zero-dimensional radical ideal. Examples for random dense polynomials: much faster than Maple (root finding or regular chains). Let  $B = nD(D - 1)^n$ , then depends on  $B^{3t}$ . Use grevlex and generic staircase [MS03].

Main cost is given in [LSED20], depends on degree bound of minors of  $H$ . Again have much faster timings.

### 1.2 Moustrou & Reiner: Specht polynomials

Does a symmetric problem have a symmetric solution? Note the “half degree principle” from [Reiner2012].

#### 1.2.1 Q&A

**Q** Does this give you faster algorithms?

**A** We haven't got there yet.

### 1.3 Davenport

See <https://staff.bath.ac.uk/masjhd/Slides/JHDSIAMAG21Monday.pdf>.

## 1.4 Schost: Bit Complexity

Some basic questions

- Is  $V \cap \mathbf{R}^n$  empty
- Find a point in each real-connected component (we focus on this).
- Many operations have algebraic complexity  $d^{O(n)}$  or  $d^{O^\sim(n)}$ .
- We would hope that complexity is  $O^\sim(h) \times$  algebraic complexity

There is good bit complexity for infinitesimal-based algorithms, but these are hard to analyse. We'll look at polar variety algorithms.

Assume radical and  $V$  is smooth and equidimensional.

**Theorem 1** *With probability  $> 1 - \epsilon$ , we can compute at least one point in each connected component with  $O^\sim(hd^n \log^2(1/\epsilon))$ .*

Idea based on [SEDS03]. In generic coordinates, our system has finitely many solutions. need to prove that the unlucky substitutions lie in a suitable subvariety etc. Need a constructive version of Thom's transversality theorem.

Need a construction from [Giusti et al 1997].

# Chapter 2

## August 17

### 2.1 Christina Katsamaki: Algorithms and Algebraic Operations on Parametric Curves

Two problems

#### 2.1.1 Topology of a parametric curve

Well-studied in 2D [KS14].

### 2.2 Agnes Szanto: Smooth Points on Real Algebraic Sets

$\dim_{\mathbf{C}}(V)$  is  $d^{O(n)}$ , but  $r := \dim_{\mathbf{R}}(V)$  is  $d^{O(r(n-r))}$  — gap here.

Finding smooth points in each component: many works. [BPR06, Chapter 13] in general. Critical point methods are only guaranteed to work for smooth varieties. For real dimension, see [LSED21] for the latest.

**Theorem 2** *Assume  $V(f_1, \dots, f_s)$  is equidimensional of dimension  $n - s$ . Suppose the polynomial  $g$  has  $\text{Sing}(V) \cap \mathbf{R}^n \subset V(g)$  and  $\dim(V \cap V(g)) < n - s$ . Then the set of points where  $g|_{V \cap \mathbf{R}^n}$  attains its extreme values on every component of  $V \cap \mathbf{R}^n$ .*

[MorkPiene2008] example where we can't get smooth points on all four components.

**Example 1 (Kuramoto  $n = 4$ )** *Discriminant  $D(w)$  has degree 48. Bézout is  $47^3 > 100K$ , reduced by symmetry to 6400, and verified real solutions numerically.*

**Theorem 3** ([Marshall2008])  $\dim_{\mathbf{R}} = \dim_{\mathbf{C}}$  iff there is a smooth point on  $V \cap \mathbf{R}^n$ .

If this doesn't work, replace  $V$  by a smaller  $V'$  with the same real points: limit of perturbed (in the sense of small  $\epsilon > 0$ ) polar varieties.

Future work is removing some of these assumptions. See [HHS20].

## 2.3 Alicia Dickenstein: Sign Conditions for the Existence of at Least One Positive Solution of a Sparse Polynomial System

See [BDG19]. Let  $a_1, \dots, a_n$  be the support of the sparse system. We would like an algorithm with sufficient conditions to predict the answer. Let  $C$  be the matrix of coefficient. We need  $\mathbf{0} \in$  positive cone spanned by columns of  $C$ . [MulleretalFOCM2016] gives a condition for  $\leq 1$  positive root. Hence the case of  $> 1$  root is more complicated.

[Conradietal, PLoS C 2017]. This generalises the Intermediate Value Theorem from  $d = 1$ .

We get a bijection between positive solutions of the original system and the solutions of the Gale dual system.

**Theorem 4 ([BDG19], Theorem 1)** *Under these assumptions,  $n_A(C) > 0$ .*

[FisherShapiro1996] has definitions of mixed and dominating matrices.

But note that when the ideal is not CM, there is no simple connection between the algebra and the geometry.

## Chapter 3

# Thursday 19th August SC<sup>2</sup> I

### 3.1 Matthew England — SC-Square: Past Successes and Future Progress with Machine Learning

Introduces SC<sup>2</sup>, and slide from [Á15]. EU project, and success at [DEG+20]. Mentions NLSAT, NuCAD, REDLOG+VeriT. MathCheck. Also many others.

#### 3.1.1 Machine Learning

Note that ML is fallible, for a variety of reasons, but for us this is bad, but not a disaster. Note that my work is not the same as the Facebook work on actually computing integrals my machine learning [KTYF21, ?]. Note [XHHLB08] on Satzilla. Many successes.

#### 3.1.2 My work

Own example of 3 cells versus 59 in 2D. [HEW+14] showed ML can do better than any one. Still don't do as well as a human heuristic. But problem is having enough, and varied enough, datasets.

#### 3.1.3

**PF** Can you get heuristics a human can understand, e.g. reverse engineering?

**A** Tried this — not particularly successful. We had a human-understandable set of features, though.

## 3.2 Baptiste Vergain: Decidable Logics with Arithmetic and Uninterpreted Symbols for SMT

Note work in progress. We are at the frontier of decidability. In particular difference logic with unary predicates.  $x - y\sigma c$  with  $\sigma \in \{=, \neq, <, >, \leq, ge\}$ . Therefore can define parity. On  $\mathbf{N}$  this is equivalent to S1S (Büchi automata). Existential quantification is automaton projection.

Extension to  $\mathbf{Z}$  uses the usual  $\mathbf{N} \leftrightarrow \mathbf{Z}$  bijection: the automata are bigger. But  $\mathbf{R}$  is different. Example which is true  $< a$  and chaos  $> a$ . Examples of operators on behaviours.

### 3.2.1

**MJB** Examples in this subset? It is implementable with existing quantifier techniques?

**A-PF** Not really example-driven.

**MJB** If this automaton can do quantifier instantiation, this would be helpful.

**Q-JHD** Q?

**A** Probably like **R**. Grant Passmore claims equisatisfiability.

## 3.3 Grant Olney Passmore: An Introduction to the Imandra Automated Reasoning System

Note IJCAR systems paper. A new(ish) theorem prover based on OCAML<sup>1</sup>. Sales pitch: “A new cloud-native automated reasoning system”.

We have an axiomatic semantics for a subset of OCAML. Extreme focus on automation. A key idea is “first class counterexamples”: common in algebra. A conjecture about a program is itself a program. Hence we ask “does this always evaluate to true”. Hence a counter-example is a finite call graph. We have a variety of mechanisms for connecting tools.

Interactive example, showing finding a counterexample of a polymorphic statement falsified: synthesising a function and its type. Another example (reverse of reverse) : “no counterexamples  $< 100$ , so ask for a proof”. So does a proof.

### 3.3.1 Q&A

**Q-MJB** What theories?

**A** We are guided by UNSAT cores in SMT, so need that. We have some SMT solvers ourselves, but also a plug-in system for other solvers.

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<sup>1</sup>“Widely used in finance” — see §3.3.2: also Coq.

### 3.3.2 “Widely used in Finance”

JHD asked Grant to expand on this.

“Re OCaml, yes it is widely used in finance. A few examples:

1. Bloomberg Terminals ship with the LexiFI suite for describing and pricing structured products (derivatives). This is written in OCaml, and the DSL for describing derivatives is actually a collection of OCaml combinators.
2. Jane Street is a major prop trading shop which uses OCaml
3. Goldman Sachs, Citi, Itiviti, OneChronos, etc., all use OCaml through their use of Imandra :-).”

JHD regards (1) as particularly telling. [https://en.wikipedia.org/wiki/Bloomberg\\_Terminal](https://en.wikipedia.org/wiki/Bloomberg_Terminal) claims “As of October 2016, there were 325,000 Bloomberg Terminal subscribers worldwide”. The current version of Bloomberg’s corporate information makes the same claim.

## 3.4 Martin Brain: Further Steps Down The Wrong Path: Improving Multiplication in Bit-Blasting

Bitblasting takes QF-bitvectors (i.e.  $\mathbf{Z}/2^n$ ) into booleans. Tables of various operators, and whether propositionally-complete. Multipliers are quadratic, and not propositionally complete, which is a worry. The smallest encoding is  $O(n \log n)$  but propositionally complete is  $2^n$ . However, I will talk about it. Example reducing  $975 \times N$  from seven additions to two. Good general example. Then shows a real example of a NN with 36 multiplies by constants (note that we’re allowed to share subterms). But it’s NP-complete, so we have an NP to feed to an NP SAT solver!

Multiplication by Polynomial Interpolation. Note that we can pick nice evaluation points, e.g. 0, 1,  $-1$ . Substantial savings.

### 3.4.1 Q&A

**Q-PF** How much can you leave out if . . . .

**A** You can leave some out, but I’d like to have a better theory.

## Chapter 4

# Friday 20th August SC<sup>2</sup> II

### 4.1 Michela Ceria: Degroebnerization and Its Applications: a New Approach for Reverse Engineering of Gene Regulatory Networks

Only need linear algebra. See [LS04]. Have various coordinate functions, which can be viewed as polynomials. Need normal forms of polynomials, which they propose to get via GB. Quadratic in #variables, exponential in #Points.

#### 4.1.1 Q&A

**Brandilyn** What is the role of the bars?

**A** The bar ( $k$ th bar) represents degree  $k$  of the corresponding monomial. This essentially computes a lex basis.

**Q** Other basis?

**A** Not yet.

**Brandilyn**

### 4.2 Alexei Lisitsa: Constraint Satisfaction for Gauss Diagrams Enumeration

How to extract Gauss diagram from a curve. The interlacement graph: nodes connected if corresponding edges in Gauss diagram intersect. A diagram is prime iff interlacement graph is connected. Diagrams are equivalent if diagram graphs isomorphic. Then Gauss asked which chord diagrams are realisable by planar graphs. Gauss had a necessary condition. Sufficient conditions by [Dehn1936].

Claims that these can be formulated in terms of interlacement graph: [Rozen-thiel1976]. The GL- and B- conditins have no second-order quantification.

But even with simple symmetry breaking, time grows fast (miniZinc solver).

Hence we have an on-the-fly checker in SWi-Prolog. Direct and incremental algortihms implemented. There is a bijection between  $S_n$  and even/odd matchings. A prime Gauss diagram  $n$  which is not a wheel can be generated from an  $n - 1$  prime diagram by a teepee move.

Note that we have mistakes in main theorems of papers in IJKTR (? were these GL and B?): counterexamples start at  $n = 9$  and many for larger  $n$ . See [KLLV21].

But quantified SAT would allow for direct implementation of [Rozen-thiel1976].

#### 4.2.1 Q&A

**MJB** Would “search over non-isomorphic graphs” be a useful primitive?

**A** Yes, very much.

### 4.3 Jasper Nalbach: Extending the Fundamental Theorem of Linear Programming for Strict Inequalities

Simplex for lazy SMT [DdM06] but no proof. [KingPhD2014] gave a proof. We generalise this.

Lazy SMT and Theory solvers. Because of negation, we need to handle weak constraints. Formally  $\leq$  suffices.  $\max_x c^T \cdot x | u \cdot x \leq b$  is our optimisation problem.  $C$  is satisfiable iff there’s a satisfying vertex.

Add a weakening  $\epsilon$ . What to prove  $\alpha \models C \Leftrightarrow \alpha \models C_w \wedge \epsilon > 0$ .

But there can be some combinatorial explosion if adding  $\epsilon$  increased  $\tilde{v}$ ertices.

#### 4.3.1 Q&A

**Q–JHD** MIP?

**A** Related, but we generally need more theory.

### 4.4 Philippe Specht: Level-Wise Construction of a Single Cell in Cylindrical Algebraic Decomposition

Given a set of constraints, and a sample point, construct a cell which is sign-invariant for the polynomials. Consider mcSAT [JdM13].

We start levelwise, substituting all of teh sample point except for  $x_n$ , so we get a cell in the  $n$ th dimension. Then iterate.

Also refinement-based CAD [BK15]. Used 11512 benchmarks from SMTLIB QF\_NRA. They solve 9293 and 9303 problems respectively, but intersection in 4227. On these level-wise is 7% faster.

## Chapter 5

# Friday 20th August SC<sup>2</sup> III

### 5.1 Zak Tonks: Practical Evaluation of QE Methods

Talk given by Ali Uncu.

#### 5.1.1 Q&A

**Q–ME** What is the ECh heuristic — how is this relevant to the others, which are variable orderings not EC-ordering.

**A–JHD** ECh heuristic is Algorithm 36 in Zak’s thesis. It’s a variant of Brown, aimed at cases where there are ECs as well.

### 5.2 Akshar Nair: Equational Constraints, the Lazard Projection and the Curtain Problem

#### 5.2.1 Q&A

**Q–CWB** If there are no equational constraints, do you need all the lc, tc and disc from  $A$  rather than  $E$  (which you certainly need)?

**A** I think that’s right.

### 5.3 Christopher Brown: Avoiding Work in CAD: NLSAT, CDCAC, NuCAD, etc.

Very inspired by NLSAT [JdM13] and CAC [ADEK20]. How does this relate to NuCAD [Bro15]? CAD: Projection gives us 2K polynomials, degree up to 27,

1986 cells in  $\mathbf{R}^1$ . But NLSAT has 8 open cells, others 15 or 31. Note also that if you're looking for open cells, we can ignore end-points.

**Example 2 (NLSAT)** *Choose  $x = 0$ ,  $y = 0$  gives UNSAT (odd negation of the contradiction), so  $y = -1$ , and get another cell. Eventually rules out  $x = 0$ , and we try a different  $x$ .*

**Example 3 (CDCAC)** *Having failed  $x = 0$ , we look at the projections of the polynomials, and get a bad interval for  $x$ . Note that there are (implicit) cells. But at a new  $x = 1$ , say, we also sample  $y = 0$  and find the same conflict (whereas NLSAT would have generalised).*

**Example 4 (NuCAD)** *We keep a priority queue of unanalysed cells. As CDCAC have to do the splits multiple times.*

All three are conflict-guided, which means we're lazy w.r.t. projection. But note that they all trade this for a more complicated SMT-like control mechanism, especially NLSAT. NLSAT builds complete cells as it goes, whereas CDCAC will only have a complete cell with SAT. NuCAD doesn't allow overlap, but it doesn't have cylindricity constraints.

There are commonalities: fixed variable ordering, and some cell orientation.

### 5.3.1 Q&A

**Q-JHD** Always end up with the same SAT sample point?

**A** Not quite a coincidence - I made the same "arbitrary" choices.

## 5.4 Vijay Ganesh: Logic Solvers and Machine Learning: The Next Frontier

CWB pointed out the range of arbitrary choices, and ML is a way of addressing this. SAT solvers currently are a soup of heuristics: which actually matter? I want to view solvers as proof systems, with a natural way of using ML. There are a range of branching heuristics. We regard these as heuristics to maximise global learning rate.

Example of variable choice as multi-armed bandits. Look at results from various arms, and use exponential moving averages. Then apply RL here. Example: between "A assigned" and "A unassigned" is used in 2 out of 3 learns. Then do exponential moving averages on this ratio, to decide best variables. Shows cactus plot, with his MiniSAT+LRB beating standard MiniSAT.

But is global learning rate the best thing? Seems to be.

This is not the whole reason why SAT solvers do well, especially on industrial instances.

#### 5.4.1 Q&A

Q

A

# Bibliography

- [Á15] E. Abraham. Building Bridges between Symbolic Computation and Satisfiability Checking (slides). *Invited Talk at ISSAC 2015*, 2015.
- [ADEK20] E. Abraham, J.H. Davenport, M. England, and G. Kremer. Deciding the Consistency of Non-Linear Real Arithmetic Constraints with a Conflict Driven Search Using Cylindrical Algebraic Coverings. *To appear in Journal of Logical and Algebraic Methods in Programming*, 2020.
- [BDG19] F. Bihan, A. Dickenstein, and M. Giaroli. Sign conditions for the existence of at least one positive solution of a sparse polynomial system. <https://arxiv.org/abs/1908.05503>, 2019.
- [BK15] C. Brown and M. Košta. Constructing a single cell in cylindrical algebraic decomposition. *J. Symbolic Computation*, 70:14–48, 2015.
- [BPR06] S. Basu, R. Pollack, and M.-F. Roy. Algorithms in Real Algebraic Geometry, 2nd ed. *Springer*, 2006.
- [Bro15] C.W. Brown. Open Non-uniform Cylindrical Algebraic Decompositions. In *Proceedings ISSAC 2015*, pages 85–92, 2015.
- [DdM06] B. Dutertre and L. de Moura. A fast linear-arithmetic solver for DPLL (T). In *International Conference on Computer Aided Verification*, pages 81–94, 2006.
- [DEG<sup>+</sup>20] J.H. Davenport, M. England, A. Griggio, T. Sturm, and C. Tinelli, editors. *Symbolic Computation and Satisfiability Checking: special issue of Journal of Symbolic Computation*, volume 100, 2020.
- [HEW<sup>+</sup>14] Z. Huang, M. England, D. Wilson, J.H. Davenport, L.C. Paulson, and J. Bridge. Applying machine learning to the problem of choosing a heuristic to select the variable ordering for cylindrical algebraic decomposition. In S.M.Watt *et al.*, editor, *Proceedings CICM 2014*, pages 92–107, 2014.

- [HHS20] K. Harris, J.D. Hauenstein, and A. Szanto. Smooth Points on Semi-algebraic Sets. <https://arxiv.org/abs/2002.04707>, 2020.
- [JdM13] D. Jovanović and L. de Moura. Solving non-linear arithmetic. *ACM Communications in Computer Algebra*, 46(3/4):104–105, 2013.
- [KLLV21] A. Khan, A. Lisitsa, V. Lopatkin, and A. Vernitski. Circle graphs (chord interlacement graphs) of Gauss diagrams: Descriptions of realizable Gauss diagrams, algorithms, enumeration. <https://arxiv.org/abs/2108.02873>, 2021.
- [KS14] A. Kobel and M. Sagraloff. On the Complexity of Computing with Planar Algebraic Curves. *To appear in J. Complexity*, 2014.
- [KTYF21] H. Kubota, Y. Tokuoka, T.G. Yamada, and A. Funahashi. Symbolic integration by integrating learning models with different strengths and weaknesses. <https://arxiv.org/abs/2103.05497>, 2021.
- [LMP21] H.P. Le, D. Manevich, and D. Plaumann. Computing totally real hyperplane sections and linear series on algebraic curves. <https://arxiv.org/abs/2106.13990>, 2021.
- [LS04] R. Laubenbacher and B. Stigler. A computational algebra approach to the reverse engineering of gene regulatory networks. *Journal of Theoretical Biology*, 229:523–537, 2004.
- [LSED20] H.P. Le and M. Safey El Din. Solving parametric systems of polynomial equations over the reals through Hermite matrices. <https://arxiv.org/abs/2011.14136>, 2020.
- [LSED21] P. Lairez and M. Safey El Din. Computing the dimension of real algebraic sets. <https://arxiv.org/abs/2105.10255>, 2021.
- [MBD<sup>+</sup>18] C.B. Mulligan, R. Bradford, J.H. Davenport, M. England, and Z. Tonks. Quantifier Elimination for Reasoning in Economics. <https://arxiv.org/abs/1804.10037>, 2018.
- [MS03] G. Moreno-Socías. Degrevlex Gröbner bases of generic complete intersections. *Journal of Pure and Applied Algebra*, 180:263–283, 2003.
- [SEDS03] M. Safey El Din and É. Schost. Polar Varieties and Computation of One Point in Each Connected Component of a Smooth Real Algebraic Set. In J.R. Sendra, editor, *Proceedings ISSAC 2003*, pages 224–231, 2003.
- [XHHLB08] L. Xu, F. Hutter, H.H. Hoos, and K. Leyton-Brown. SATzilla: Portfolio-based Algorithm Selection for SAT. *Journal of Artificial Intelligence Research*, 32:565–606, 2008.