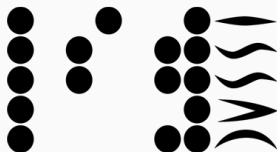


Condition Numbers for the Cube.

I: Univariate Polynomials and Hypersurfaces

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This presentation is about the accepted paper

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I: Univariate Polynomials and Hypersurfaces

authored by

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The long-term goal

Grid and subdivision methods: What are they for?

Grid methods:

- Feasibility of real polynomial systems (Cucker & Smale; 1999)
- Approximating and counting real zeros (Cucker, Krick, Malajovich & Wschebor; 2008, 2009, 2012)
- Homology of real algebraic sets (Cucker, Krick & Shub; 2012)
- Homology of semialgebraic sets (Bürgisser, Cucker & Lairez; 2018) (Bürgisser, Cucker & T.-C.; ISSAC'19, 2020+)

Subdivision methods:

- Root isolation of univariate polynomials (Pan, Davenport, Yap, Sagraloff, Mehlhorn, Rouillier, Mourrain, Yakoubsohn...) **Too many to write them all!**
- Root isolation of polynomial systems (Dedieu & Yakoubsohn; 1991) (Mourrain & Pavone; 2009) (Mantzaflaris, Mourrain & Tsigaridas; 2011)
- PL approximation of curves and surfaces (Plantinga & Vegter; 2004) (Galehouse; 2009) (Burr, Gao & Tsigaridas; ISSAC'17)

Grid and subdivision methods: What is their complexity?

Techniques for controlling complexity:

- Root separation bounds (Davenport, Mahler & Mignotte) (Emiris, Mourrain & Tsigaridas; ISSAC'10) → **Bit-complexity bounds**
- Variety separation bounds (D'Andrea, Krick & Sombra; 2013) (Burr, Gao & Tsigaridas; ISSAC'17) → **Bit-complexity bounds**
- Continuous amortization (Burr, Kraemer & Yap; 2009) (Burr; 2016) + Condition-based complexity + Probabilistic analysis (Cucker, Ergür & T.-C.; ISSAC'19, 2020+) → **Average and smoothed complexity bounds**

Average and smoothed complexity bounds!

MAIN ISSUE:

Condition numbers are designed for the sphere,
but the algorithms work in the cube!

Example:

Covering the cube efficiently is easy,
but covering the sphere is not so easy.

Condition numbers for the cube?
THAT IS OUR OBJECTIVE!



The plan

$$\begin{aligned} \text{Geometry on the sphere} &= \text{Euclidean norm} & \|x\| &:= \sqrt{\sum_i |x_i|^2} \\ \text{Geometry on the cube} &= \infty\text{-norm} & \|x\|_\infty &:= \max_i |x_i| \end{aligned}$$

Goal:

$$\begin{aligned} \text{Geometry on the sphere} &\rightarrow \text{Geometry on the cube} \\ \text{Euclidean norm} &\rightarrow \infty\text{-norm} \end{aligned}$$

Warning: The ∞ -norm does not come from an inner product!

Hopes:

- Better complexity estimates
- Faster algorithms
- Better understanding of subdivision methods

Antecedent exploring other norms: (Cucker, Ergür & T.-C.; SIAM AG'19)

- Condition theory for hypersurfaces in the cube
- Gaussian polynomials
- Polynomials with restricted support (up to assumptions)

We showcase our results with:

- Separation bounds for roots of univariate polynomials in $(0, 1)$
- Plantinga-Vegter algorithm

Polynomial inequalities and condition

Norm for polynomials control evaluations, variations...



Condition-based complexity theory

Our choice:

$$\|f\|_1 := \sum_{\alpha} |f_{\alpha}|$$

the 1-norm for polynomials

Why?: $\|f\|_1$ behaves like the dual of $\|x\|_{\infty}$

$f \in \mathcal{P}_{n,d} := \{g \in \mathbb{R}[X_1, \dots, X_n] \mid \deg g \leq d\}$, $x, y \in I^n := [-1, 1]^n$, $v \in \mathbb{R}^n$

- Control of the evaluation

$$|f(x)| \leq \|f\|_1$$

- Control of the derivative I

$$\|\langle \nabla f, v \rangle\|_1 \leq d \|f\|_1 \|v\|_\infty$$

- Control of the derivative II

$$\|\nabla_x f\|_1 \leq d \|f\|_1$$

- Lipschitz properties for f and its derivatives

$$\begin{aligned} |f(x) - f(y)| &\leq d \|f\|_1 \|x - y\|_\infty \\ \|\nabla_x f - \nabla_y f\|_1 &\leq d(d-1) \|f\|_1 \|x - y\|_\infty \end{aligned}$$

Definition (T.-C., Tsigaridas; ISSAC'20)

Let $f \in \mathcal{P}_{n,d}$ and $x \in I^n$, the *local condition number of f at x* is the quantity

$$C(f, x) := \frac{\|f\|_1}{\max \left\{ |f(x)|, \frac{1}{d} \|\nabla_x f\|_1 \right\}}.$$

Important observation: $C(f, x) = \infty$ iff x is a singular zero of f

Properties of the local condition number

- **Regularity inequality**

either $|f(x)|/\|f\|_1 \geq 1/C(f, x)$ or $\|\nabla_x f\|_1/(d\|f\|_1) \geq 1/C(f, x)$.

- **1st Lipschitz property**

$f \mapsto \|f\|_1/C(f, x)$ is 1-Lipschitz

- **2nd Lipschitz property**

$I^n \ni x \mapsto 1/C(f, x)$ is d -Lipschitz

- **Condition Number Theorem**

$$\|f\|_1/\text{dist}_1(f, \Sigma_x) \leq C(f, x) \leq 2d \|f\|_1/\text{dist}_1(f, \Sigma_x)$$

where $\Sigma_x := \{g \in \mathcal{P}_{n,d} \mid x \text{ is a singular zero of } g\}$

- **Higher Derivative Estimate.** If $C(f, x)|f(x)|/\|f\|_1 < 1$, then

$$\gamma(f, x) \leq \frac{1}{2}(d-1)\sqrt{n} C(f, x).$$

where $\gamma(f, x)$ is Smale's γ

All we need for condition-based complexity analyses!

Application 1: Separation of roots

Separation of roots

Recall...

$$\Delta_{\alpha}(f) := \text{dist}(\alpha, f^{-1}(0) \setminus \{\alpha\})$$

Theorem (T.-C. & Tsigaridas; ISSAC'20)

Let $f \in \mathcal{P}_{1,d}$. Then, for every complex $\alpha \in f^{-1}(0)$ such that $\text{dist}(\alpha, l) \leq 1/(3(d-1)C(f))$,

$$\Delta_{\alpha}(f) \geq \frac{1}{16(d-1)C(f)}$$

where

$$C(f) := \sup_{x \in l} C(f, x).$$

I.e., the condition number controls the separation of the roots

Probabilistic results

Randomness model I: Two properties

(SG) We call a random variable \mathfrak{x} *subgaussian*, if there exist a $K > 0$ such that for all $t \geq K$,

$$\mathbb{P}(|\mathfrak{x}| > t) \leq 2 \exp(-t^2/K^2).$$

The smallest such K is the *subgaussian constant* of \mathfrak{x} .

(AC) A random variable \mathfrak{x} has the *anti-concentration property*, if there exists a $\rho > 0$, such that for all $\varepsilon > 0$,

$$\max\{\mathbb{P}(|\mathfrak{x} - u| \leq \varepsilon) \mid u \in \mathbb{R}\} \leq 2\rho\varepsilon.$$

The smallest such ρ is the *anti-concentration constant* of \mathfrak{x} .

Randomness model II: Zintzo random polynomials I

Definition (T.-C. & Tsingaridas; ISSAC'20)

Let $M \subseteq \mathbb{N}^n$ be a finite set such that $0, e_1, \dots, e_n \in M$. A *zintzo random polynomial* supported on M is a random polynomial

$$f = \sum_{\alpha \in M} f_{\alpha} X^{\alpha} \in \mathcal{P}_{n,d}$$

such that the coefficients f_{α} are independent subgaussian random variables with the anti-concentration property.

Note: 'zintzo', from Basque, means honest, upright, righteous.

Observation: No scaling in the coefficients, as it happens with dobro random polynomials (Cucker, Ergür & T.-C.; ISSAC'19)

Randomness model II: Zintzo random polynomials II

For \mathfrak{f} a zintzo random polynomial, we define:

1. the *subgaussian constant* of \mathfrak{f} which is given by

$$K_{\mathfrak{f}} := \sum_{\alpha \in M} K_{\alpha}, \quad (4.1)$$

where K_{α} is the subgaussian constant of \mathfrak{f}_{α} , and

2. the *anti-concentration constants* of \mathfrak{f} which is given by

$$\rho_{\mathfrak{f}} := \sqrt[n+1]{\rho_0 \rho_{e_1} \cdots \rho_{e_n}}, \quad (4.2)$$

where ρ_0 is the anti-concentration constant of \mathfrak{f}_0 and for each i , ρ_{e_i} is the anti-concentration constant of \mathfrak{f}_{e_i} .

$K_{\mathfrak{f}} \rho_{\mathfrak{f}}$ will control the complexity estimates

Randomness model II: Zintzo random polynomials III

Let $M \subseteq \mathbb{N}^n$ be such that it contains $0, e_1, \dots, e_n$. These are two important cases of zintzo random polynomials:

G A *Gaussian polynomial supported on M* is a zintzo random polynomial f supported on M , the coefficients of which are i.i.d. Gaussian random variables.

In this case, $\rho_f = 1/\sqrt{2\pi}$ and $K_f \leq |M|$.

U A *uniform random polynomial supported on M* is a zintzo random polynomial f supported on M , the coefficients of which are i.i.d. uniform random variables on $[-1, 1]$.

In this case, $\rho_f = 1/2$ and $K_f \leq |M|$.

Randomness model III: Smoothed case

Proposition (T.-C. & Tsigaridas; ISSAC'20)

Let \mathfrak{f} be a zintzo random polynomial supported on M , $f \in \mathcal{P}_{n,d}$ a polynomial supported on M , and $\sigma > 0$. Then,

$$\mathfrak{f}_\sigma := f + \sigma \|f\|_1 \mathfrak{f}$$

is a zintzo random polynomial supported on M such that

$$K_{\mathfrak{f}_\sigma} \leq \|f\|_1 (1 + \sigma K_{\mathfrak{f}}) \text{ and } \rho_{\mathfrak{f}_\sigma} \leq \rho_{\mathfrak{f}} / (\sigma \|f\|_1).$$

In particular,

$$K_{\mathfrak{f}_\sigma} \rho_{\mathfrak{f}_\sigma} = (K_{\mathfrak{f}} + 1/\sigma) \rho_{\mathfrak{f}}.$$

I.e., the smoothed case is included in our average case!

Theorem (T.-C. & Tsigaridas; ISSAC'20)

Let $f \in \mathcal{P}_{n,d}$ a zintzo random polynomial supported on M . Then for all $t \geq e$,

$$\mathbb{P}(C(f, x) \geq t) \leq \sqrt{nd}^n |M| (8K_f \rho_f)^{n+1} \frac{\ln^{\frac{n+1}{2}} t}{t^{n+1}}.$$

Corollary (T.-C. & Tsigaridas; ISSAC'20)

Let $f \in \mathcal{P}_{n,d}$ be a zintzo random polynomial supported on M . Then, for all $t > 2e$,

$$\mathbb{P}(C(f) \geq t) \leq \frac{1}{4} \sqrt{nd}^{2n} |M| (64K_f \rho_f)^{n+1} \frac{\ln^{\frac{n+1}{2}} t}{t}.$$

Application 2: Plantinga-Vegter algorithm

The complexity estimate

We had...

Theorem (Cucker, Ergür & T.-C.; ISSAC'19, 2020+)

Let $f \in \mathcal{P}_{n,d}$ be a dobro random polynomial with parameters K and ρ .

The average number of boxes of the final subdivision of Plantinga-Vegter algorithm on input f is at most

$$d^n N^{\frac{n+1}{2}} 2^{15n \log n + 12} (K\rho)^{n+1}$$

where $N := \dim \mathcal{P}_{n,d}$.

We get...

Theorem (T.-C. & Tsigaridas; ISSAC'20, 2020+)

Let $f \in \mathcal{P}_{n,d}$ be a zintzo random polynomial supported on M . The

average number of boxes of the final subdivision of the Plantinga-Vegter algorithm on input f is at most

$$n^2 d^{2n} |M| \left(4\sqrt{n+1} K_f \rho_f \right)^{n+1}.$$

Corollary (T.-C. & Tsigaridas; ISSAC'20, 2020+)

Let $f \in \mathcal{P}_{n,d}$ be a random polynomial supported on M . The average number of boxes of the final subdivision of Plantinga-Vegter algorithm on input f is at most

$$n^2 \left(2\sqrt{n+1}\right)^{n+1} d^{2n} |M|^{n+2}$$

if f is Gaussian or uniform.

Bere arretagatik eskerrik asko!
Ευχαριστω για την προσοχη σας!

Galderak?
Καμιά ερώτηση?