Discrete-Time and Continuous-Time Systems over the Reals: Relating Complexity with Robustness, Length and Precision

PhD Defence Manon Blanc

Jury: Enrico Formenti, Juha Kontinen, Elvira Mayordomo, Cristóbal Rojas, Pierre Valarcher





Introduction

Introduction: what are we studying?



Introduction: what are we studying?



• Continuous-Time Systems: can be described by a (continuous) ODE

$$\frac{\partial \mathbf{f}(t,\mathbf{x})}{\partial t} = \mathbf{u}(\mathbf{f}(t,\mathbf{x}),t,\mathbf{x})$$

• Discrete-Time Systems: can be described by a discrete ODE

$$\frac{\delta \mathbf{f}(n,\mathbf{y})}{\delta n} = \mathbf{f}(n+1,\mathbf{y}) - \mathbf{f}(n,\mathbf{y}) = \mathbf{u}(\mathbf{f}(n,\mathbf{y}),n,\mathbf{y})$$

f :

- - Discrete-Time Systems: can be described by a discrete ODE

$$n \to 2^n$$
 $\frac{\delta f(n, \mathbf{y})}{\delta n} = f^2(n) - f(n)$

- Characterisations of polynomial-time and polynomial-space;
- Complexity of *robust* dynamical systems;
- Robustness of tilings.

Motivations

- Verification: can a system reach an unsafe state from an initial state (reachability)
- Models of computation: what is the computational power of a given model
- Ressources: how to measure time, memory (space) used by a computation



Computer Turing machines, boolean circuits...

Example: the addition



Example: the addition



Computationnal Power: model equivalence



$[f_1, f_2, \cdots, f_k; o_1, o_2, \cdots, o_n]$

• Allows a more denotational point of view on complexity classes

$[f_1, f_2, \cdots, f_k; o_1, o_2, \cdots, o_n]$

- Allows a more denotational point of view on complexity classes
- This is already done in computability:

 $[0, \mathbf{s}, \pi; composition, minimisation, primitive recursion]$

Effective Church-Turing thesis: Every effectively and *reasonable* models of computation yields to the same complexity classes

 \rightarrow Notions of time and space do not depend on the model, up to some polynomial

 \rightarrow Verification is hard

Effective Church-Turing thesis: Every effectively and *reasonable* models of computation yields to the same complexity classes

 \rightarrow Notions of time and space do not depend on the model, up to some polynomial

 \rightarrow Verification is hard

What about continuous-time models?

- Introduced by Shannon (1941);
- Mathematical model of the Differential Analizer;
- Model based on circuits, with several interconnected units doing basic operations
- Corresponds to polynomial ODEs: y' = p(y)

$$e_1 - k - e_0$$

constant: $e_0 = ke_1$

$$e_1 = 1$$

product: $e_0 = e_1 e_2$

 $e_1 \\ e_2$ e_0 summer: $e_0 = -(e_1 + e_2)$ e(0) e_1 e_0 integrator: $e_0 = -\int_0^t (e_1(u)du + e(0))$

GPAC: how does it work?



$$\begin{cases} x'(t) = y(t) \\ y'(t) = -x(t) \\ x(0) = -1 \\ y(0) = 0 \end{cases} \Rightarrow \begin{cases} x(t) = \cos(t) \\ y(t) = -\sin(t) \\ y(t) = -\sin(t) \end{cases}$$

15



- Difficulty: simulating Turing machines with continuous settings (e.g. Graça, Rojas) with
 - generalised shifts (Moore)
 - recurrent neural networks (Siegelmann, Sontag)
 - analytic functions (Graca, Buescu, Campagnolo)
 - hydrostatic equations in Beltrami fields (Cardona, Miranda, Peralta-Salas)
 - 2d continuous PAMs (Koiran, Cosnard, Garzon)
 - ...

Solving continuous ODEs

$$\mathbf{f}(0,\mathbf{x}) = \mathbf{g}(\mathbf{x})$$
 and $\frac{\partial \mathbf{f}(t,\mathbf{x})}{\partial t} = \mathbf{u}(\mathbf{f}(t,\mathbf{x}),t,\mathbf{x}),$

• Non-computable in the general case, for **u** computable (Pour-El, Richards)

Solving continuous ODEs

$$\mathbf{f}(0,\mathbf{x}) = \mathbf{g}(\mathbf{x})$$
 and $\frac{\partial \mathbf{f}(t,\mathbf{x})}{\partial t} = \mathbf{u}(\mathbf{f}(t,\mathbf{x}),t,\mathbf{x}),$

- Non-computable in the general case, for **u** computable (Pour-El, Richards)
- Computable for **u** computable and unique solution (Collins, Graça, Ruohonen)

Solving continuous ODEs

$$\mathbf{f}(0,\mathbf{x}) = \mathbf{g}(\mathbf{x})$$
 and $\frac{\partial \mathbf{f}(t,\mathbf{x})}{\partial t} = \mathbf{u}(\mathbf{f}(t,\mathbf{x}),t,\mathbf{x}),$

- Non-computable in the general case, for **u** computable (Pour-El, Richards)
- Computable for **u** computable and unique solution (Collins, Graça, Ruohonen)
- FPSPACE-completeness on a bounded domain for **u** computable in polynomial-time (Kawamura, Ko)

But now, how do we define the complexity?

• Measuring the complexity so it corresponds to the digital world

- Time?:
 - $\rightarrow \mathsf{Time} = \mathsf{Length}$
 - Continuous ODEs : Bournez, Graça, Pouly
 - Discrete ODEs : Bournez, Durand, Kontinen, Antonelli, ...

- Time?:
 - $\rightarrow \mathsf{Time} = \mathsf{Length}$
 - Continuous ODEs : Bournez, Graça, Pouly
 - Discrete ODEs : Bournez, Durand, Kontinen, Antonelli, ...
- Space?:
 - Effective Church thesis for probabilistic systems: Rojas
 - A characterisation of PSPACE: Gozzi, Graça

 \rightarrow Our approach: Space = Precision

- Mathematical framework: Computable Analysis
- Complexity framework: Algebraic Models

- What is a computable real number x?
 - \rightarrow we can compute a representation of *x*.

- What is a computable real number x?
 - \rightarrow we can compute a representation of x.

Example

e, π are computable. $\sum_{i\geq 1}2^{-BB(i)}$, where BB is the Busy Beavers function is not.

- What is a computable real number x?
 - \rightarrow we can compute a representation of x.

Example

e, π are computable. $\sum_{i\geq 1} 2^{-BB(i)}$, where BB is the Busy Beavers function is not.

What is a computable function f : ℝ → ℝ?
 → on a representation of x ∈ ℝ, we produce a representation of f(x).

- What is a computable real number x?
 - \rightarrow we can compute a representation of x.

Example

e, π are computable. $\sum_{i\geq 1} 2^{-BB(i)}$, where BB is the Busy Beavers function is not.

- What is a computable function f : ℝ → ℝ?
 → on a representation of x ∈ ℝ, we produce a representation of f(x).
- How do we define complexity over the reals?

Algebraic Models: for complexity classes

• Characterisation of polynomial time with explicit bounds: e.g. Cobham

Algebraic Models: for complexity classes

• Characterisation of polynomial time with explicit bounds: e.g. Cobham

Here: describing complexity without explicit bounds (e.g. Bellantoni, Cook, Levant, Marion, Jacobé de Naurois, ...):

Algebraic Models: for complexity classes

• Characterisation of polynomial time with explicit bounds: e.g. Cobham

Here: describing complexity without explicit bounds (e.g. Bellantoni, Cook, Levant, Marion, Jacobé de Naurois, ...):

- With BSS model (Jacobé de Naurois, Marion, ...)
- Characterisation of FPTIME with linear length ODEs (Bournez, Durand, Kontinen, ...)
Time and Space as algebras

	With Discrete ODEs	With ODEs
FPTIME for $\mathbb{N}^{\mathbb{N}}$	(Bournez, Durand)	
$FPTIME \text{ for } \mathbb{R}^{\mathbb{N}}$	$\overline{\mathbb{LDL}^{\bullet}}$ (thm. 3.1.6)	
$FPTIME\;for\;\mathbb{R}^{\mathbb{R}}$	$\overline{\mathbb{LDL}^{\circ}}$ (thm. 3.2.3)	(Bournez, Graça, Pouly)
FPSPACE for $\mathbb{R}^{\mathbb{R}}$	$\overline{\mathbb{RLD}^{\circ}}$ (thm. 5.1.6)	$\overline{\mathbb{RCD}}$ (thm. 5.2.2)

	With Discrete ODEs	With ODEs
$FPTIME \text{ for } \mathbb{N}^{\mathbb{N}}$	(Bournez, Durand)	
FPTIME for $\mathbb{R}^{\mathbb{N}}$	$\overline{\mathbb{LDL}^{\bullet}}$ (thm. 3.1.6)	
FPTIME for $\mathbb{R}^{\mathbb{R}}$	$\overline{\mathbb{LDL}^{\circ}}$ (thm. 3.2.3)	(Bournez, Graça, Pouly)
FPSPACE for $\mathbb{R}^{\mathbb{R}}$	$\overline{\mathbb{RLD}^{\circ}}$ (thm. 5.1.6)	$\overline{\mathbb{RCD}}$ (thm. 5.2.2)

- $\overline{LDL^{\bullet}}$, $\overline{LDL^{\circ}}$ based on Linear Length ODEs;
- $\overline{\mathbb{RLD}^{\circ}}$ based on Robust Linear Discrete ODEs;
- $\overline{\mathbb{RCD}}$ based on Robust Continuous ODEs.

Definition (5.2.3) $f:\mathbb{R}\to\mathbb{R}$ is robustly ODE definable (from initial condition g, and dynamic u) if

• it is the solution of the following continuous ODE:

$$\mathbf{f}(0,\mathbf{x}) = \mathbf{g}(\mathbf{x})$$
 and $\frac{\partial \mathbf{f}(t,\mathbf{x})}{\partial t} = \mathbf{u}(\mathbf{f}(t,\mathbf{x}),t,\mathbf{x});$

• And polynomially numerically stable (to be defined : next slides)

 \rightarrow this allows computation by dichotomy.









More formally:

- $\exists \Delta \in \mathbb{Q}_+^*$, such that the previous ODE is (polynomially space) solvable on $[0, \Delta]$.
- For t ≥ Δ, we can compute f(t, x) at 2⁻ⁿ by computing some approximation f(t/2, x) of f(t/2, x) at precision 2^{-η(n)}.

We consider :

$$\overline{\mathbb{RCD}} = [\mathbf{0}, \mathbf{1}, \pi_i^k, +, -, \times, \tanh, \cos, \pi, \frac{x}{2}, \frac{x}{3};$$

composition, robust continuous ODE, ELim]

Theorem (5.2.2)

 $\overline{\mathbb{RCD}}\cap\mathbb{R}^{\mathbb{R}}=\mathsf{FPSPACE}\cap\mathbb{R}^{\mathbb{R}}$

$\overline{\mathbb{RLD}^\circ}\cap\mathbb{R}^{\mathbb{R}}=\overline{\mathbb{RCD}}\cap\mathbb{R}^{\mathbb{R}}$

• Continuous \Rightarrow Discrete settings:

From our definitions of robustness of ODEs

All the functions and operators in $\overline{\mathbb{RCD}}$ are computable in polynomial-space.

• We give *continuous* approximations of some basic functions (integer/fractional part, modulo 2, ...):

• We give *continuous* approximations of some basic functions (integer/fractional part, modulo 2, ...):





- We give *continuous* approximations of some basic functions (integer/fractional part, modulo 2, ...);
- We encode each step of the transition of the Turing machine into the algebra, using the previous functions : Next;

- We give *continuous* approximations of some basic functions (integer/fractional part, modulo 2, ...);
- We encode each step of the transition of the Turing machine into the algebra, using the previous functions : Next;
- We obtain a *robust linear discrete ODE* encoding the execution of the Turing machine: State(t + 1) = Next(State(t)) so

$$\frac{\delta \overline{State}(t, y)}{\delta t} = \overline{Next}(\overline{State}(t, y))$$

$\overline{\mathbb{RLD}^{\circ}} \cap \mathbb{R}^{\mathbb{R}} = \overline{\mathbb{RCD}} \cap \mathbb{R}^{\mathbb{R}}$

$\overline{\mathbb{RLD}^{\circ}} \cap \mathbb{R}^{\mathbb{R}} = \overline{\mathbb{RCD}} \cap \mathbb{R}^{\mathbb{R}}$

• Discrete \Rightarrow Continuous settings:

Adaptation of the a trick due to Branicky ('95)

$\overline{\mathbb{RLD}^{\circ}} \cap \mathbb{R}^{\mathbb{R}} = \overline{\mathbb{RCD}} \cap \mathbb{R}^{\mathbb{R}}$

• Discrete \Rightarrow Continuous settings:

Adaptation of the a trick due to Branicky ('95)

$$\frac{\delta f}{\delta t}(t) = u(y(t), t)$$

$$\begin{cases} z_1(0) = x_0 \\ z_2(0) = x_0 \\ \left(\frac{\partial z_2}{\partial t}(t) = c_2 \left(r(z_1(t)) - z_2(t) \right)^3 \theta \left(-\cos 2\pi t \right) \\ \frac{\partial z_1}{\partial t}(t) = c_1 \left(\bar{u} \left(r(z_2(t)) \right) - z_1(t) \right)^3 \theta \left(\cos 2\pi t \right) \end{cases}$$

Robustness in Dynamical Systems

Dynamical Systems



• Reachability is undecidable...

- Reachability is undecidable...
- ... more precisely, it is not co-computably enumerable;

- Reachability is undecidable...
- ... more precisely, it is not co-computably enumerable;
- It becomes decidable for a sub-class of systems: Robust Dynamical Systems.

- Informal conjecture: undecidability in verification does not happen for robust systems.
- Undecidabilty is related to non-robustness of the systems (Asarin, Bouajjani)

 \rightarrow with proper notion of robusteness: no sensitivity to an arbitrarly small perturbation.

Robustness in Dynamical Systems



- go from computability to complexity,
- quantifying the robustness to characterise PSPACE,
- having a notion of robustness to characterise PTIME.

Consider
$$R^{\mathcal{H}}_{\omega} = \bigcap_{\epsilon > 0} R^{\mathcal{H}}_{\epsilon}(x, y)$$

• Say
$$R^{\mathcal{H}}$$
 is robust when $R^{\mathcal{H}}_{\omega} = R^{\mathcal{H}}$:
 $R^{\mathcal{H}}$ robust $\Rightarrow R^{\mathcal{H}}$ computable.

Reachability in robust dynamical systems is *decidable* (Asarin & Bouajjani)

Theorem (4.2.33)

Take a locally Lipschitz system, with $f : X \to X$ polynomial-time computable, with X a closed rational box. Then, for $p : \mathbb{N} \to \mathbb{N}$ a polynomial, $R_p^{\mathcal{H}} \subseteq \mathbb{Q}^d \times \mathbb{Q}^d \times \mathbb{N} \in \mathsf{PSPACE}$.

 \rightarrow works also for dynamical systems over the reals

Example

Simulation of Turing machines with continuous PAMs.

Theorem (4.3.2)

Consider a dynamical system, with **f** locally Lipschitz, computable, whose domain is a computable compact, then, for all **x**, $cls(R_{\omega}^{\mathcal{H}}(\mathbf{x})) \subseteq \mathbb{R}^{d}$ is a co-computably enumerable closed subset.

Plot twist

From CA, Computable \Leftrightarrow can be plotted.



Theorem (4.3.5) $R^{\mathcal{H}}$ closed and can be plotted in a name of $\mathbf{f} \Leftrightarrow$ the system is robust, i.e. $R_{\omega}^{\mathcal{H}} = R^{\mathcal{H}}$.

Toward Complexity for tilings





Robinson



Figure 1: To the left is Robinson's tileset, where tiles can be rotated and reflected. To the right a pattern that appears in every tiling by Robinson's tileset.

- The domino problem is undecidable...
- ... more precisely, it is not computably enumerable;
- It becomes decidable for a sub-class of tilesets: robust tilesets.
 - \rightarrow Chapter 5

Conclusion
• We extended the motto **time = length** to discrete ODEs (chapter 3);

- We extended the motto **time = length** to discrete ODEs (chapter 3);
- We proved that space = precision (chapter 5);
 → proper notions of costs for analogue models of computation;

- We extended the motto **time = length** to discrete ODEs (chapter 3);
- We proved that space = precision (chapter 5);
 → proper notions of costs for analogue models of computation;
- We studied what makes reachability decidable for robust dynamical systems and prove that space complexity is linked to the precision (chapter 4);

- We extended the motto **time = length** to discrete ODEs (chapter 3);
- We proved that space = precision (chapter 5);
 → proper notions of costs for analogue models of computation;
- We studied what makes reachability decidable for robust dynamical systems and prove that space complexity is linked to the precision (chapter 4);
- We apply this principle to tilings (chapter 6).

- Minimising the algebras?
- Would it work for GPAC and polynomial ODEs?
- Can we relate this approch to second-order complexity?
- Can we relate more thinly our notions of robustness?

- Studying non-determinism, and polynomial hierarchy;
- Algebraically characterising probabilistic classes;
- Studying the complexity for more general differential equations, e.g. distributions.

We consider:

$$\overline{\mathbb{LDL}^{\bullet}} = [\mathbf{0}, \mathbf{1}, \pi_i^k, \ell(x), +, -, \times, \overline{\mathrm{cond}}(x), \frac{x}{2};$$

composition, linear length ODE, ELim]

Theorem (B., Bournez, MCU22 Best Student Paper Award)

 $\mathsf{FPTIME} \cap \mathbb{R}^{\mathbb{N}} = \overline{\mathbb{LDL}^{\bullet}} \cap \mathbb{R}^{\mathbb{N}}$

We consider:

$$\overline{\mathbb{LDL}^{\circ}} = [\mathbf{0}, \mathbf{1}, \pi_i^k, \ell(x), +, -, \tanh, \frac{x}{2}, \frac{x}{3};$$

composition, linear length ODE, ELim]

Theorem (B., Bournez, MFCS23 Best Paper Award) $\overline{\mathbb{LDL}^{\circ}} \cap \mathbb{R}^{\mathbb{R}} = \mathsf{FPTIME} \cap \mathbb{R}^{\mathbb{R}}$ We consider:

$$\overline{\mathbb{RLD}^{\circ}} = [\mathbf{0}, \mathbf{1}, \pi_i^k, \ell(n), +, -, \tanh, \frac{x}{2}, \frac{x}{3};$$

composition, robust linear ODE, ELim]

Theorem (B., Bournez, MFCS23 Best Paper Award)

 $\overline{\mathbb{RLD}^{\circ}} \cap \mathbb{R}^{\mathbb{R}} = \mathsf{FPSPACE} \cap \mathbb{R}^{\mathbb{R}}$

Appendix: An unusual way of solving an ODE

- Computation at t = x at precision 2^{-n} , with initial condition t = 0
- Computation at t = t₀ + ^x/₂ at precision 2^{-η(n)}, with initial condition t₀ = 0 and t₀ = ^x/₂
- Computation at $t = t_0 + \frac{x}{4}$ at precision $2^{-\gamma(n)}$, with initial condition $t_0 = 0$ and $t_0 = \frac{x}{4}$ and $t_0 = \frac{x}{2}$ and $t_0 = \frac{3x}{4}$