

*A new method for the reconstruction of  
rational functions*

**Xiao Liu**

University of Oxford

Based on e-print: [2306.12262](#)

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# Outline

**I. Introduction**

**II. The method**

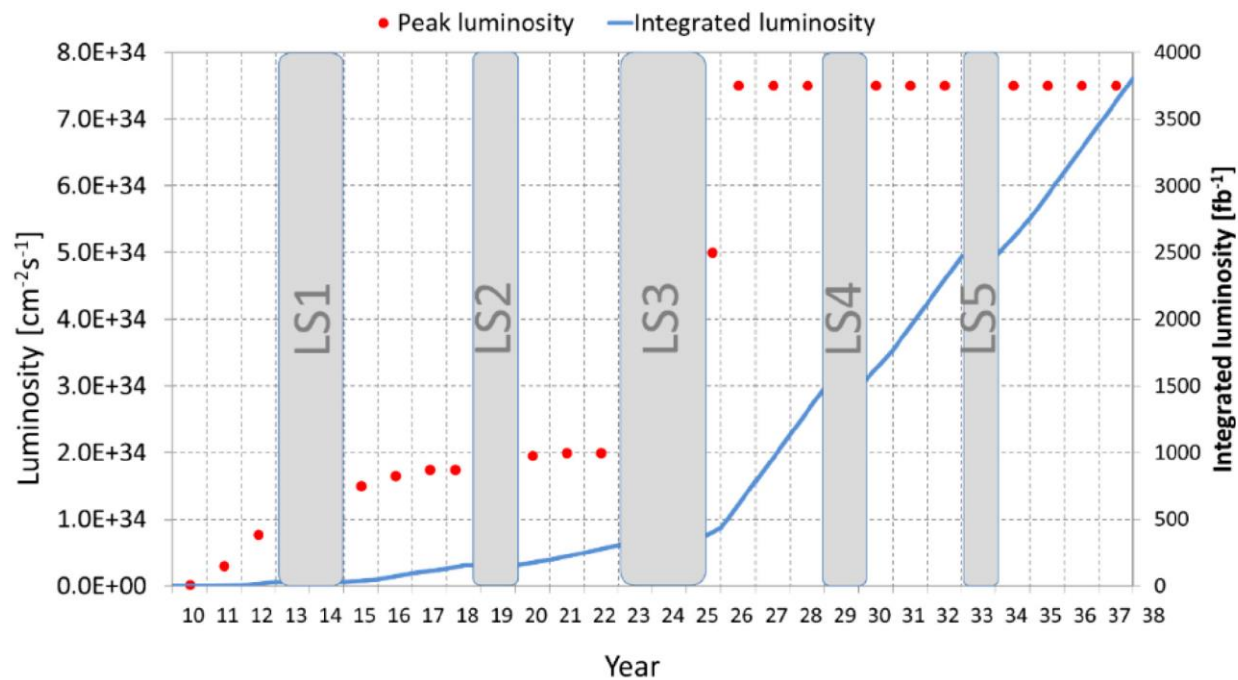
**III. Examples**

**IV. Summary and outlook**

# High precision particle physics

## ➤ Era of Precision

- Theoretical predictions & experimental measurements
- Test particle physics Standard Model & probe signals of New Physics
- Higher order corrections required



\*Figure from [Apollinari, Alonso, Bruning, et al, 2015]

# High precision particle physics

## ➤ Multiloop scattering amplitudes

- Construct the amplitude

$$A = \sum c_i I_i$$

- $I_i$ : scalar Feynman integrals in **dimensional regularization**

$$I(\vec{\nu}) = \int \prod_{i=1}^L \frac{d^D \ell_i}{i\pi^{D/2}} \frac{\mathcal{D}_{K+1}^{-\nu_{K+1}} \cdots \mathcal{D}_N^{-\nu_N}}{(\mathcal{D}_1 + i0)^{\nu_1} \cdots (\mathcal{D}_K + i0)^{\nu_K}}$$

- Compute the scalar integrals: **reduction + computation**

- reduction: express all the scalar integrals in terms of a smaller set of independent integrals (**master integrals**)

$$I_i = \sum_j b_{ij} M_j$$

- computation: compute the master integrals as expansions in the dimensional regulator  $\epsilon = (4 - D)/2$

$$M_j = \sum_{l=-2L} d_{jk} \epsilon^k$$

# Feynman integrals

## ➤ Integration-by-parts (IBP) reduction [Chetyrkin and Tkachov, Nucl. Phys. B, 1981] [Laporta, Int. J. Mod. Phys. A, 2000]

$$0 = \int \prod_{i=1}^L \frac{d^D \ell_i}{i\pi^{D/2}} \frac{\partial}{\partial \ell_j^\mu} \left( \frac{v_k^\mu}{\mathcal{D}_1^{\nu_1} \dots \mathcal{D}_m^{\nu_m}} \right)$$

- Number of master integrals is finite. [Smirnov and Petukhov, Lett. Math. Phys., 2011]
- Computer programs
  - AIR [Anastasiou and Lazopoulos, JHEP, 2004] FIRE [Smirnov, JHEP, 2008] [Smirnov, Smirnov, Comput. Phys. Commun., 2013] [Smirnov, Comput. Phys. Commun., 2015] [Smirnov and Chuharev, Comput. Phys. Commun., 2020] Reduze [Studerus, Comput. Phys. Commun., 2010] [Manteuffel and Studerus, e-Print: 1201.4330]
  - Kira [Maierhofer, Usovitsch and Uwer, Comput. Phys. Commun., 2018] [Klappert, Lange, Maierhofer and Usovitsch, Comput. Phys. Commun., 2021] LiteRed [Lee, 2012] [Lee, 2014] NeatIBP [Wu, Boehm, Ma, et al, 2305.08783]

# Finite field techniques

## ➤ Finite field arithmetic [Manteuffel and Schabinger, Phys. Lett. B, 2015] [Peraro, JHEP, 2016]

- Motivation: to avoid intermediate expression swelling
  - numerical sampling + reconstruction over finite fields
- Univariate polynomials: Newton's interpolation formula

$$f(x) = a_0 + (x - x_0) \left( a_1 + (x - x_1) \left( a_2 + (x - x_2) \left( \cdots + (x - x_{R-1}) a_R \right) \right) \right)$$

- Univariate rational functions: Thiele's interpolation formula

$$f(x) = a_0 + (x - x_0) \left( a_1 + (x - x_1) \left( a_2 + (x - x_2) \left( \cdots + \frac{x - x_{R-1}}{a_R} \right)^{-1} \right)^{-1} \right)^{-1}$$

- Multivariate polynomials: recursively applying Newton's formula
- Multivariate rational functions
  - univariate rational functions + multivariate polynomials
- Programs: FiniteFlow [Peraro, JHEP, 2019] FireFly [Klappert and Lange, Comput. Phys. Commun., 2020]



# Summary

Refined IBP systems:

syzygy equations [Gluza, Kajda and Kosower, Phys. Rev. D, 2011] [Larsen and Zhang, Phys. Rev. D, 2016]

block-triangular systems [Guan, XL, Ma, Chin.Phys.C, 2020]

More powerful linear solver:


Kira [Maierhofer, Usovitsch and Uwer, Comput. Phys. Commun., 2018]

RATRACER [Magerya, e-Print: 2211.03572]

Better interpolation methods [Klappert and Lange, Comput.Phys.Commun. 2020] [Belitsky, Smirnov, Yakovlev, 2023.02511]

More compact ansatz [Badger, Hansen, Chicherin, et al, JHEP 2021] [Laurentis, Page, JHEP 2022] [Abreu, Laurentis, Ita, et al, 2305.17056]

The method in this talk


$$\text{time} = \frac{\text{time for a single sample} \times \text{number of samples}}{\text{number of CPUs}}$$

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# Motivation

## ➤ A simple observation

- Traditional strategy: reconstructing functions individually & neglecting common structures
- Example

$$f_i(x) = \left( \frac{1+x}{1-x} \right)^{i-1}, \quad i \in [1, 100]$$

- approximately 200 samples using Thiele's interpolation formula
- linear relations

$$(1-x)f_{i+1}(x) - (1+x)f_i(x) = 0, \quad i \in [1, 99]$$

- ansatz + linear fit → 4 samples

$$(a_i + b_i x)f_{i+1}(x) + (c_i + d_i x)f_i(x) = 0$$

- Linear relations → common structures utilized → number of samples reduced

# The method

## ➤ General description

- Goal: all  $n - 1$  independent relations among  $k$ -variate functions  $f_1(\vec{x}), \dots, f_n(\vec{x})$
- Ansatz

$$Q_1(\vec{x})f_1(\vec{x}) + \dots + Q_n(\vec{x})f_n(\vec{x}) = 0$$

- $Q_i(\vec{x})$ : polynomial of  $\vec{x} \Rightarrow$  specifying monomials  $x_1^{\alpha_1} \dots x_k^{\alpha_k}$
- Definition 1:

$$P(\{x_{i_1}, \dots, x_{i_l}\}, m) := \{x_{i_1}^{\alpha_1} \dots x_{i_l}^{\alpha_l} \mid \sum \alpha_i \leq m\}$$

- $P(\{x_1\}, 0) = \{1\}$ ;  $P(\{x_1\}, 2) = \{1, x_1, x_1^2\}$ ;  $P(\{x_2, x_3\}, 1) = \{1, x_2, x_3\}$
- Definition 2:

$$P_1 \times P_2 := \{p_1 p_2 \mid p_1 \in P_1, p_2 \in P_2\}$$

- $P(\{x_1\}, 2) \times P(\{x_2, x_3\}, 1) = \{1, x_1, x_1^2, x_2, x_1 x_2, x_1^2 x_2, x_3, x_1 x_3, x_1^2 x_3\}$

# The method

- Divide variables  $\vec{x}$  into  $r$  subsets  $S_1, \dots, S_r$ 
  - 3-variate example:  $S_1 = \{x_1\}, S_2 = \{x_2, x_3\}$
- For a specific  $Q_i(\vec{x})$ , given integers  $\vec{z} = \{z_1, \dots, z_r\}$

$$M(\vec{z}) := P(S_1, z_1) \times \cdots \times P(S_r, z_r)$$

- In practice: use **the same  $\vec{z}$**  for all the  $Q$ 's
  - $\vec{z} = \{0,0\} \rightarrow M(0,0) = \{1\} \rightarrow a_1 f_1 + \cdots + a_n f_n = 0$
  - $\vec{z} = \{1,0\} \rightarrow M(1,0) = \{1, x_1\} \rightarrow (b_1 + c_1 x_1) f_1 + \cdots + (b_n + c_n x_1) f_n = 0$
  - $\vec{z} = \{0,1\} \rightarrow M(0,1) = \{1, x_2, x_3\} \rightarrow (d_1 + e_1 x_2 + g_1 x_3) f_1 + \cdots = 0$
- **Generalized algorithm from [Guan, XL, Ma, Chin.Phys.C, 2020]**
  - 1. start with  $\sum z_i = 0$ ;
  - 2. for each solution of  $\vec{z}$ , make the ansatz and fit the unknowns
  - 3. test the number of independent relations: if sufficient, terminate; otherwise increase  $\sum z_i$  by 1 and go back to step 2.

# Summary

- Summary
  - build a generator of the numerical samples for the target functions
    - e.g., IBP system + linear solver
  - find the system of all the independent linear relations over a finite field
    - various ansatz of  $Q_1(\vec{x})f_1(\vec{x}) + \cdots + Q_n(\vec{x})f_n(\vec{x}) = 0$
    - linear fit = samples ( $N_{\text{sample}} \sim N_{\text{unknown}}$ ) + dense solve ( $N_{\text{sample}} \times N_{\text{unknown}}$ )
  - solve the linear system to obtain explicit solutions
    - traditional rational functions reconstruction strategy
    - additional finite fields + rational numbers reconstruction (Chinese Remainder Theorem + Wang's algorithm)

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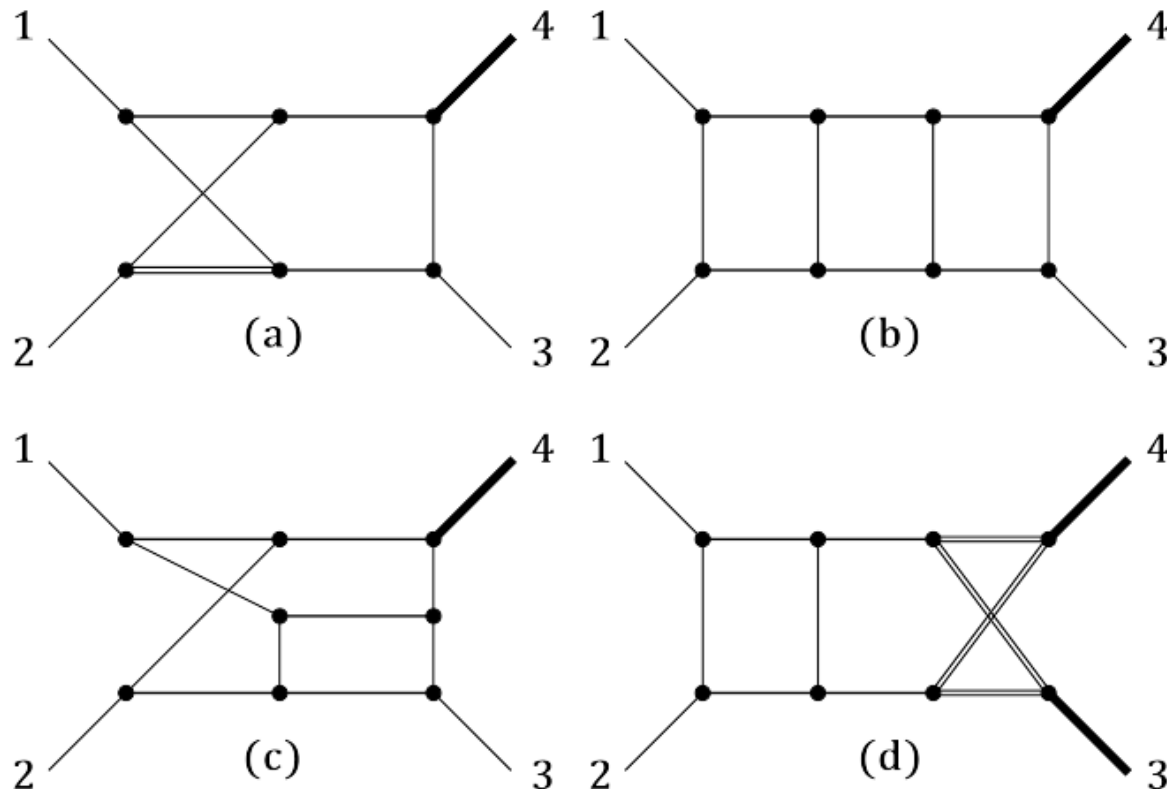
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# Examples

- Reduction coefficients of Feynman integrals or amplitudes

$$\mathcal{A} = f_1 \mathcal{M}_1 + \cdots + f_n \mathcal{M}_n$$

- a common set of denominators reflecting the singularities
- auxiliary function  $f_{n+1} = 1$





# Examples

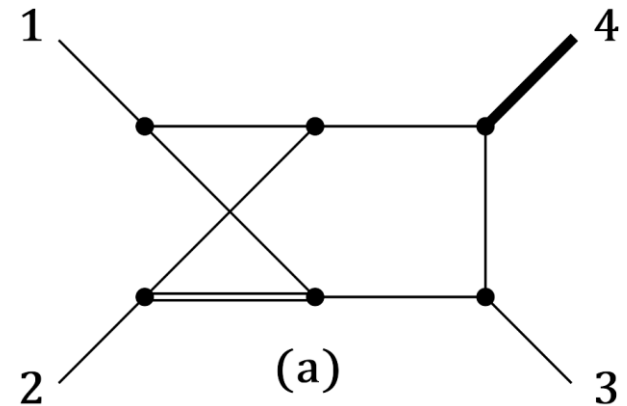
- Topology (a): two-loop amplitude of the mixed QCD-electroweak correction to  $pp \rightarrow Z + j$  [Bargiela, Caola, Chawdhry, XL, to appear]

- Setup

- $m_Z^2 = 1, m_W^2 = 7/9$
- remaining:  $\{\epsilon, s_{12}, s_{13}\}$
- 56 master integrals  $\Rightarrow$  56 rational functions
- LiteRed + FiniteFlow

- Details

- $S_1 = \{\epsilon\}, S_2 = \{s_{12}, s_{13}\}$
- $z_1 + z_2 = 6$
- 1+2 finite fields with 64-bit prime numbers
- samples:  $18326 \times 3 \rightarrow 2199 + 1561 \times 2 \Rightarrow$  a factor of 10.3
- computational cost:  $4.6\text{h} \rightarrow 0.44\text{h} + 0.03\text{h} \Rightarrow$  a factor of 9.8



# Examples

$\vec{z}$	$N_{\text{unknown}}$	$N_{\text{sample}}$	$N_{\text{relation}}$	$N_{2\text{sample}}$
{0,0}	57	58	0	-
{1,0}	114	115	0	-
{0,1}	171	172	1	4
{2,0}	171	172	0	-
{1,1}	340	341	0	-
{0,2}	339	340	1	9
{3,0}	228	229	0	-
...				
{2,2}	1014	1015	1	31
...				
{2,3}	1680	1681	20	1394
...				
{3,3}	2198	2199	33	1561
<b>summary</b>		<b>2199</b>	<b>56</b>	<b>1561</b>

# Examples

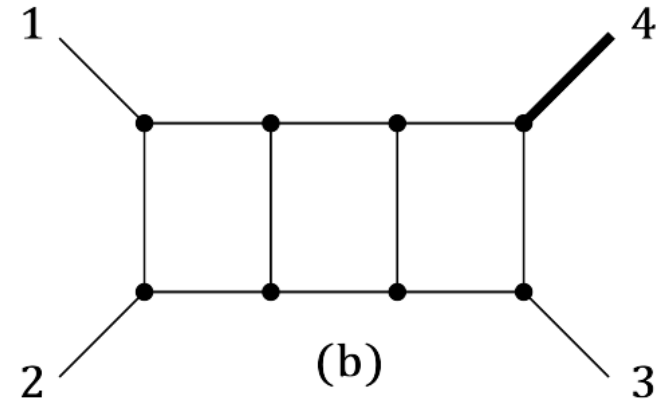
- Topology (b): an integral with rank-6 numerator

- Setup

- $p_4^2 = 1$
- remaining:  $\{\epsilon, s_{12}, s_{13}\}$
- 83 master integrals  $\Rightarrow$  83 rational functions
- NeatIBP + FiniteFlow

- Details

- $S_1 = \{\epsilon\}, S_2 = \{s_{12}, s_{13}\}$
- $z_1 + z_2 = 8$
- 1+2 finite fields
- samples:  $48574 \times 3 \rightarrow 6010 + 4599 \times 2 \Rightarrow$  a factor of 9.6
- computational cost:  $78.5\text{h} \rightarrow 8.03\text{h} + 0.12\text{h} \Rightarrow$  a factor of 9.6



# Examples

- Topology (c): differential equations of master integrals w.r.t. Mandelstam

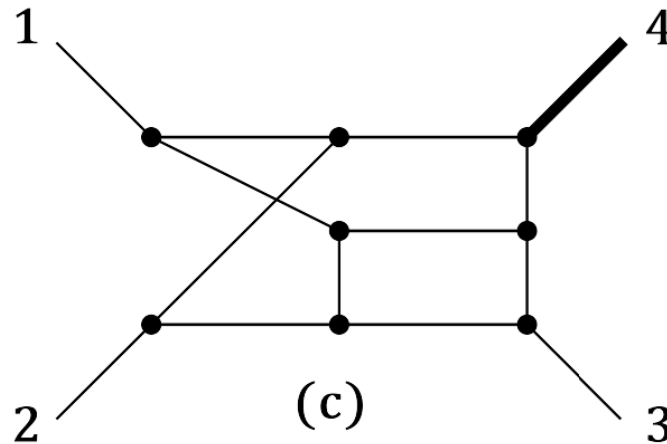
variables [Kotikov, Phys. Lett. B, 1991] [Henn, Phys. Rev. Lett., 2013] :  $\frac{\partial}{\partial s_{12}} \vec{M}, \frac{\partial}{\partial s_{13}} \vec{M}$

- Setup

- $p_4^2 = 1$
- remaining:  $\{\epsilon, s_{12}, s_{13}\}$
- 280 master integrals
- LiteRed + FiniteFlow

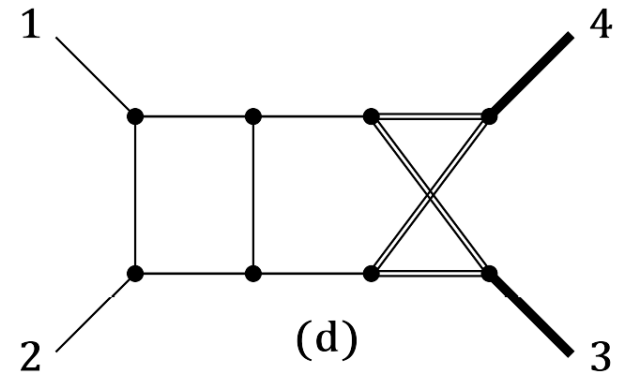
- Details

- $S_1 = \{\epsilon\}, S_2 = \{s_{12}, s_{13}\}$
- $z_1 + z_2 \leq 8$
- 1+5 finite fields
- samples:  $391937 \times 6 \rightarrow 9612 + 6810 \times 5 \Rightarrow$  a factor of 54
- computational cost:  $450728h^* \rightarrow 8369h + 180h \Rightarrow$  a factor of 53



# Examples

- Topology (d): differential equations with respect to internal squared masses
- Extensively involved in the auxiliary mass flow method [XL, Ma, Wang, Phys.Lett.B., 2018] [XL, Ma, Comput.Phys.Commun., 2023]
- Setup
  - $p_3^2 = p_4^2 = 1, s_{12} = 10, s_{13} = -22/9$
  - remaining:  $\{\epsilon, m^2\}$
  - 336 master integrals
  - LiteRed + FiniteFlow
- Details
  - $S_1 = \{\epsilon\}, S_2 = \{m^2\}$
  - $z_1 + z_2 \leq 5$
  - 1+32 finite fields
  - samples:  $14362 \times 33 \rightarrow 1414 + 1248 \times 32 \Rightarrow$  a factor of 11.5
  - computational cost:  $3230h \rightarrow 281h + 59h \Rightarrow$  a factor of 9.5



# Examples

- More details






Topology	$d_{\text{Num}}$	$d_{\text{Den}}$	$d_{\text{Rel}}$	$N_{\text{IBP}}$	$N_{\text{Rel}}$	$t_{\text{IBP/s}}$	$t_{\text{Rel/s}}$
(a)	40	39	6	34336	56	0.3	0.00075
(b)	56	55	8	200074	83	1.9	0.0024
(c)	102	103	8	3461628	280	690	0.013
(d)	144	143	5	625070	336	24.5	0.019





- degree of polynomials reduced
  - number of samples reduced
- size of system reduced
  - time for explicit solutions negligible





# Examples









- <https://gitlab.com/xiaoliu222222/examples-for-rational-functions-reconstruction>
  - explicit reduction coefficients & the linear system they satisfy


**E** **Examples for rational functions reconstruction**  Project ID: 46991632    Star 0  Fork 0






 3 Commits  1 Branch  0 Tags  67 MiB Project Storage

 **update\_readme**  
Xiao Liu authored 2 weeks ago e1b09927 

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 README  Add LICENSE  Add CHANGELOG  Add CONTRIBUTING  Enable Auto DevOps  Add Kubernetes cluster  Set up CI/CD  Add Wiki

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Name	Last commit	Last update
 a	initialize	3 weeks ago
 b	initialize	3 weeks ago
 c	initialize	3 weeks ago
 d	initialize	3 weeks ago
 README.md	update_readme	2 weeks ago

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# Summary and Outlook

- A new method for the reconstruction of rational functions is proposed, which works by exploiting all the independent linear relations among the target functions.
- Better scaling behavior
  - improvement factor: univariate  $\leq$  2-variate  $\leq$  3-variate
- The current form of the method is not so good to solve problems with more than 3 variables  $\rightarrow$  linear fit becomes dominant and sometimes prohibitive
  - refined ansatz for the relations: sparse or semi-sparse?
  - refined choice of auxiliary functions, rather than a naïve  $f_{n+1}(x) = 1$
- $t_{\text{sol}} \ll t_{\text{sam}}$  in most cases  $\Rightarrow$  improvements in the generators
  - for cases where  $t_{\text{sol}} \geq t_{\text{sam}}$ , refined approach to grouping the functions

***Thank you!***

# The method

- Redundant relations: relations from  $\vec{z}$  will be redundantly obtained from  $\vec{z}'$  if  $z_i \leq z'_i$  for any  $i$ 
  - $z_1 = 1, z_2 = 0$ :  $(x_1 - 1)f_1 + (3x_1 + 2)f_2 + \dots = 0$
  - $z_1 = 1, z_2 = 1$ :  $(x_1x_2 - x_2)f_1 + (3x_1x_2 + 2x_2)f_2 + \dots = 0$
- Solution: eliminate “solvable” monomials
  - $z_1 = 1, z_2 = 0$ :  $x_1$  of  $f_1$  is “solved”,  $x_1f_1 = f_1 + (-3x_1 - 2)f_2 + \dots$
  - $z_1 = 1, z_2 = 1$ :  $x_1$  and  $x_1x_2$  of  $f_1$  should be “solvable”
  - in general, eliminate  $\Lambda_i(\vec{z}) \times M(\vec{z}' - \vec{z})$  for all possible  $\vec{z}$
- Comment on the variables division
  - any division works:  $S_1 = \{x_1, \dots, x_k\}; S_1 = \{x_1\}, \dots, S_k = \{x_k\}; \dots$
  - but the number of samples can vary significantly
  - do some tests to gain insights