# Uncovering Singularities in Feynman Integrals via Machine Learning

The 5<sup>th</sup> Symposium on Quantum Field Theory and its Applications

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Based on arXiv:2510.10099, in collaboration with Yingxuan Xu & Yang Zhang



# **Introduction on Symbology**

About Feynman integrals, canonical differential equations and their symbol letters.

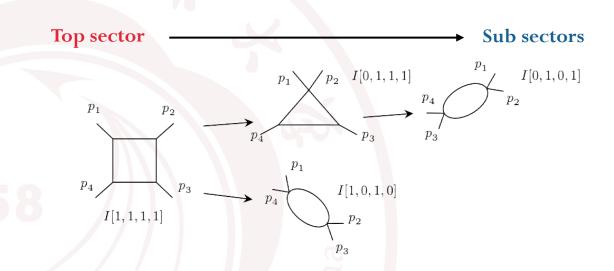
# Feynman Integrals and their Family Structure

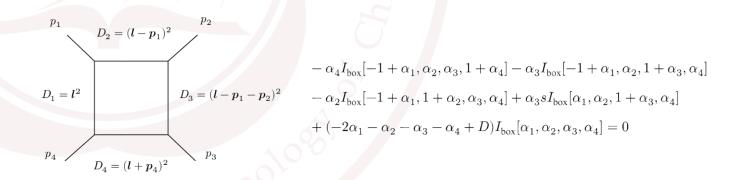
**Feynman Integrals** can be **recursively built** from top sector to sub sectors

• Form a **family structure**, in which integrals are determined by combination of propagators.

The well-known **IBP relations**[F, Tkachov, 1981] uncover the **linear relations** between different integrals

 One can determine a basis in respect to linear relations – the Master Integrals





# **Canonical Differential Equations**

Taking **derivatives** for master integrals in respect to kinematic variables lead to a differential equation system.

$$\boldsymbol{I}(s,t,\varepsilon) = \{I_{\text{box}}[0,1,0,1], I_{\text{box}}[1,0,1,0], I_{\text{box}}[1,1,1,1]\}$$



$$\boldsymbol{I} = \varepsilon^2 \exp(\varepsilon \gamma_E) (-s)^\varepsilon \begin{pmatrix} \frac{1-2\varepsilon}{\varepsilon} I_{\text{box}}[0,1,0,1] \\ \frac{1-2\varepsilon}{\varepsilon} I_{\text{box}}[1,0,1,0] \\ st I_{\text{box}}[1,1,1,1] \end{pmatrix}$$



$$rac{\partial}{\partial x_i} oldsymbol{I}(oldsymbol{x}, arepsilon) = arepsilon oldsymbol{M}_i(oldsymbol{x}) oldsymbol{I}(oldsymbol{x}, arepsilon)$$

$$\boldsymbol{M}(x) = \begin{pmatrix} -\frac{1}{x} & 0 & 0\\ 0 & 0 & 0\\ \frac{2}{x(x+1)} & -\frac{2}{x+1} & -\frac{1}{x(x+1)} \end{pmatrix}$$

Change to **Canonical Basis**, one obtain **E**-factorized Canonical Differential Equations[J. Henn, 2013]

Sometimes this can be very complicated because of complicated function space, see [\varepsilon-collaboration, 2025]

# **Symbol Letters**

$$rac{\partial}{\partial x_i} m{I}(m{x}, arepsilon) = arepsilon m{M}_i(m{x}) m{I}(m{x}, arepsilon)$$

$$\boldsymbol{M}(x) = \begin{pmatrix} -\frac{1}{x} & 0 & 0\\ 0 & 0 & 0\\ \frac{2}{x(x+1)} & -\frac{2}{x+1} & -\frac{1}{x(x+1)} \end{pmatrix}$$

$$W_i = P \in \mathbb{Q}[x_i]$$

parity even letter

$$W_i = rac{\sqrt{P} - Q}{\sqrt{P} + Q}, \quad P,Q \in \mathbb{Q}[x_i]$$

parity odd letter

$$M(x) = \sum_i a_i \operatorname{d} \log \overline{W_i}, \qquad a_i \in \mathbb{Q}^{n imes n}$$

### **Symbol letters**

- Symbol Alphabet = {All Symbol Letters}
- Very **limited** for a certain family!

**CDE Matrix** contains different **Symbol letters**, revealing the **analyticity**(poles, regions) of Feynman Integrals.

- Ingredients for <u>analytical bootstrap</u> on Feynman Integrals or Amplitudes[Carrolo, Chicherin, Henn, Yang, Zhang, 2025]
- Cluster Algebra structures [Pokraka, Spradlin, Anastasia, Weng, 2025] from Mathematical Physics

Some previous algorithms to generate **Symbol letters**:

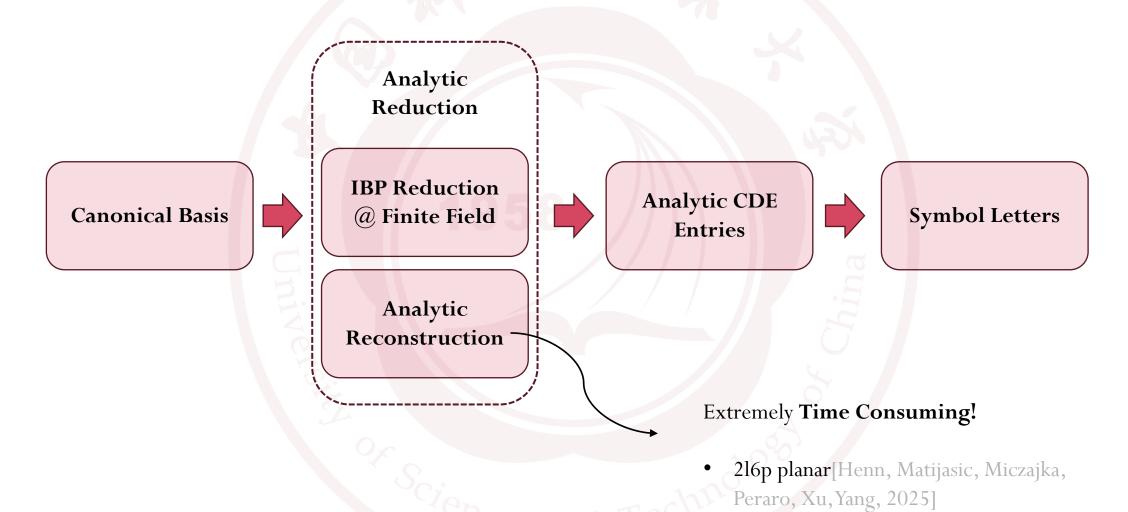
- Effortless[Antonela, 2024] and SOFIA[Correia, Giroux, Mizera, 2025], using Landau analysis and some conjectures.
- BaikovLetter[Jiang, Lian, Yang, 2024]
  using Baikov Rep.+ Maximal Cut. 5



# **Machine Learning And Symbolic Regression**

An introduction about Machine Learning and Symbolic Regression.

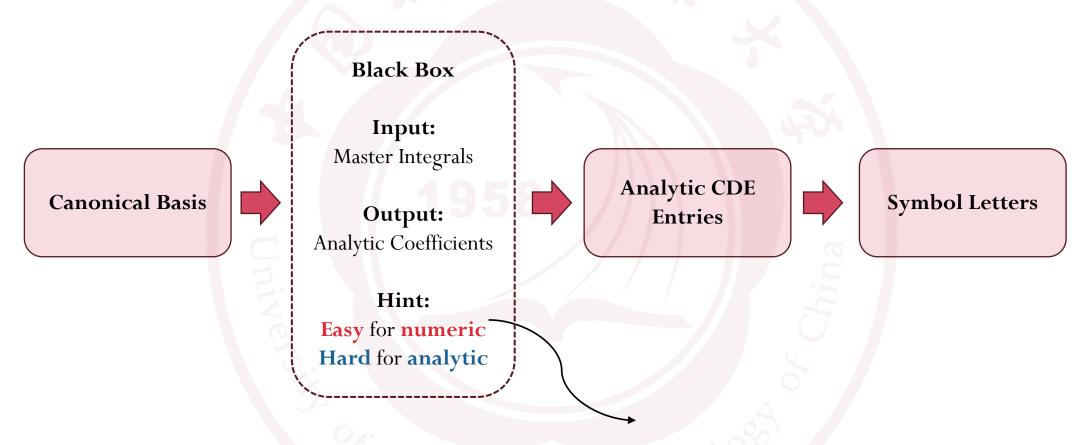
# Why Symbolic Regression?



2 hrs/pt for numerical CDE matrix

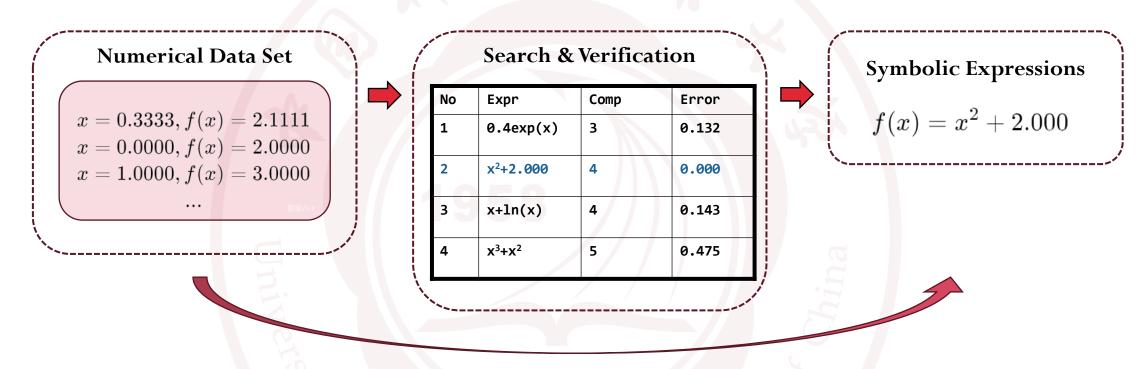
Unable to reconstruct all letters!

# Why Symbolic Regression?



This is a typical Symbolic Regression task!

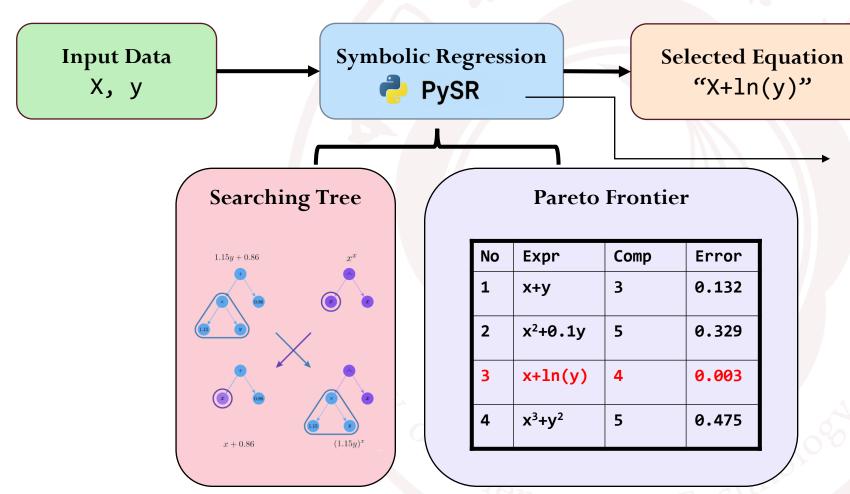
# Machine Learning: Symbolic Regression



**Symbolic Regression**: Search interpretable **symbolic expressions** from **numerical samplings**. Various Routings:

- PySR[M.Cranmer, 2023]—Genetic Programming,
- SymbolicGPT[Valipour, Panju, You, Ghodsi, 2021]—LLM based,
- IdeaSearch-Fit[Song, Cai, Zhang, Wei, Pan et.al, 2025]—GP + LLM based mixing strategy...

# Machine Learning: Symbolic Regression



**PySR** is a powerful **Symbolic Regression** toolkit.

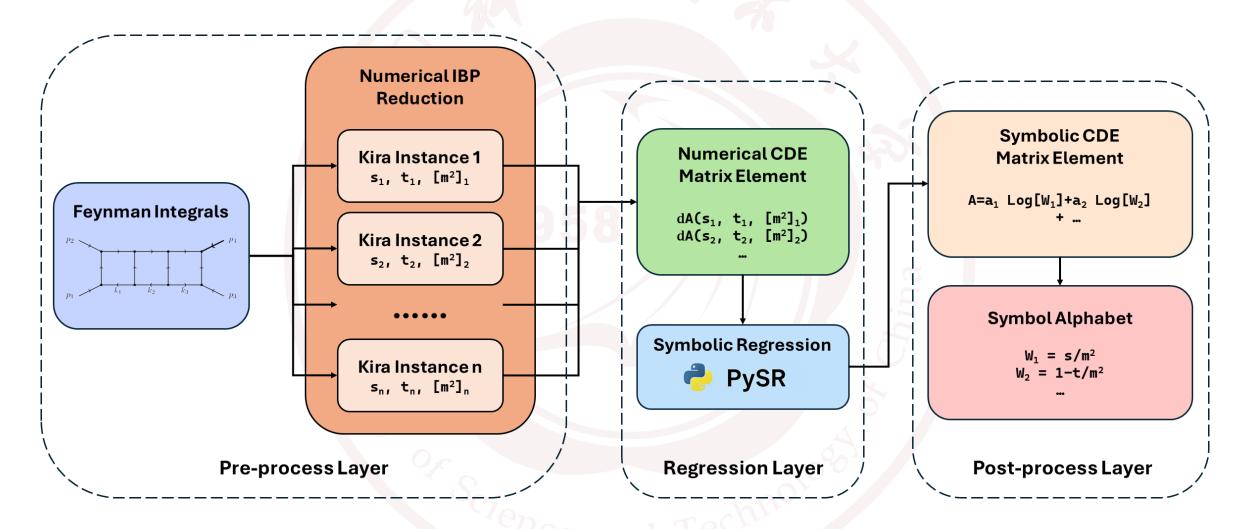
- No pre-train: Based on Genetic Programming. <u>Easy to use</u>, no GPU requirement.
- Efficiency & Accuracy: Pareto Frontier from complexity and accuracy.
- Sufficient Extension: Support Julia & Python <u>user-defined functions</u>, and many <u>advanced math operations</u>...



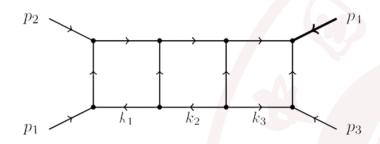
# **Apply Machine Learning to Symbol Alphabet**

Detailed workflows and examples for Symbol Alphabet building.

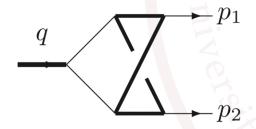
### **Workflow Introduction**



# Examples: 3l4p1m & 2l3p1m-np



 $p_4$  has mass  $m^2$ , others are massless.



q has mass s, others are massless. 4 propagators with coincide mass. 3l4p1m[Vita, Matrolia, Schubert, Yundin, 2014]

- 83MIs, 2(+1) scales:  $x=s/m^2$ ,  $y=t/m^2$
- 6 different Symbol letters—all successfully built!
- KIRA reduction:
  - Num:~20mins 12 threads of i9-13950HX CPU @ 5.30GHz
  - Ana:  $\sim$ 100mins 12 threads

$$W_i = \{x, 1 - x, y, 1 - y, x + y, 1 - x - y\}$$

### 2l3p1m-np[Manteuffel, Tancredi, 2017]

- 9MIs(sub-topology), 1(+1) scales: x=s/m<sup>2</sup>
- 5 different Symbol letters—all successfully built!
- Letters have square roots!
- KIRA reduction:
  - Num:~10mins 12 threads of i9-13950HX CPU @ 5.30GHz
  - Ana:  $\sim$ 60mins 12 threads

$$W_i = \{\sqrt{x}, \sqrt{x+4}, \sqrt{x-4}, \frac{1}{2}(\sqrt{x}+\sqrt{x+4}), \frac{1}{2}(\sqrt{x}+\sqrt{x-4})\}$$

# Trials on more Diagrams...

$\#  ext{Loop} \setminus  ext{Family}$	1 Scale 3p1m,4p0m	2 Scales 4p1m	3 Scales 4p2m	5 Scales 5p0m	5+ Scales 5p1m, 6p0m
1	<b>√√</b>	<b>√</b> √	<b>√</b> √	$\checkmark$	$\checkmark$
2	<b>√</b> √	<b>√</b> √	<b> </b>	$\checkmark$	×
3	<b>√</b> √	$\checkmark\checkmark$	$\checkmark\checkmark$	$\checkmark$	
4	<b>√</b> √				

√ ∴ Complete Symbol Alphabet reconstructed;

✓ : All Even Letters obtained, remaining ones (Odd Letters) can be constructed manually;

: Some letters not found;

— : Not tested because of incomplete reference.

### 315p-PBB family

[Liu, Matijasic, Miczjka, YX. Xu, YQ. Xu, Zhang, 2024]

316MIs, 5 scales 20+1 Even Letters Found.

10 Odd Letters manually built.

### Discussions and Future...

### Unlike traditional Machine Learning project...

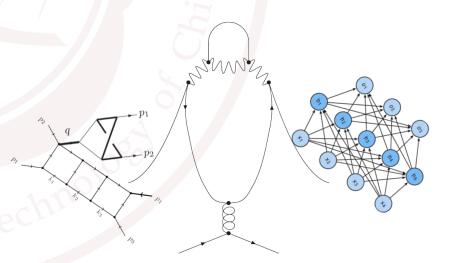
• We pursue a completely exact solution, instead of approximate computation.

### To achieve this...

- We "weirdly" tune Hyper-parameter to "force" the model over-fitting;
- We also perform an **early-terminate** as soon as **exact solution comes up**.

### In the future...

- Improve accuracy and efficiency?
- New areas for AI-ML to obtain exact & closed form solution?
- . . . . .





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