Adventures with Agentic AI (in particle physics)

BNL Seminar

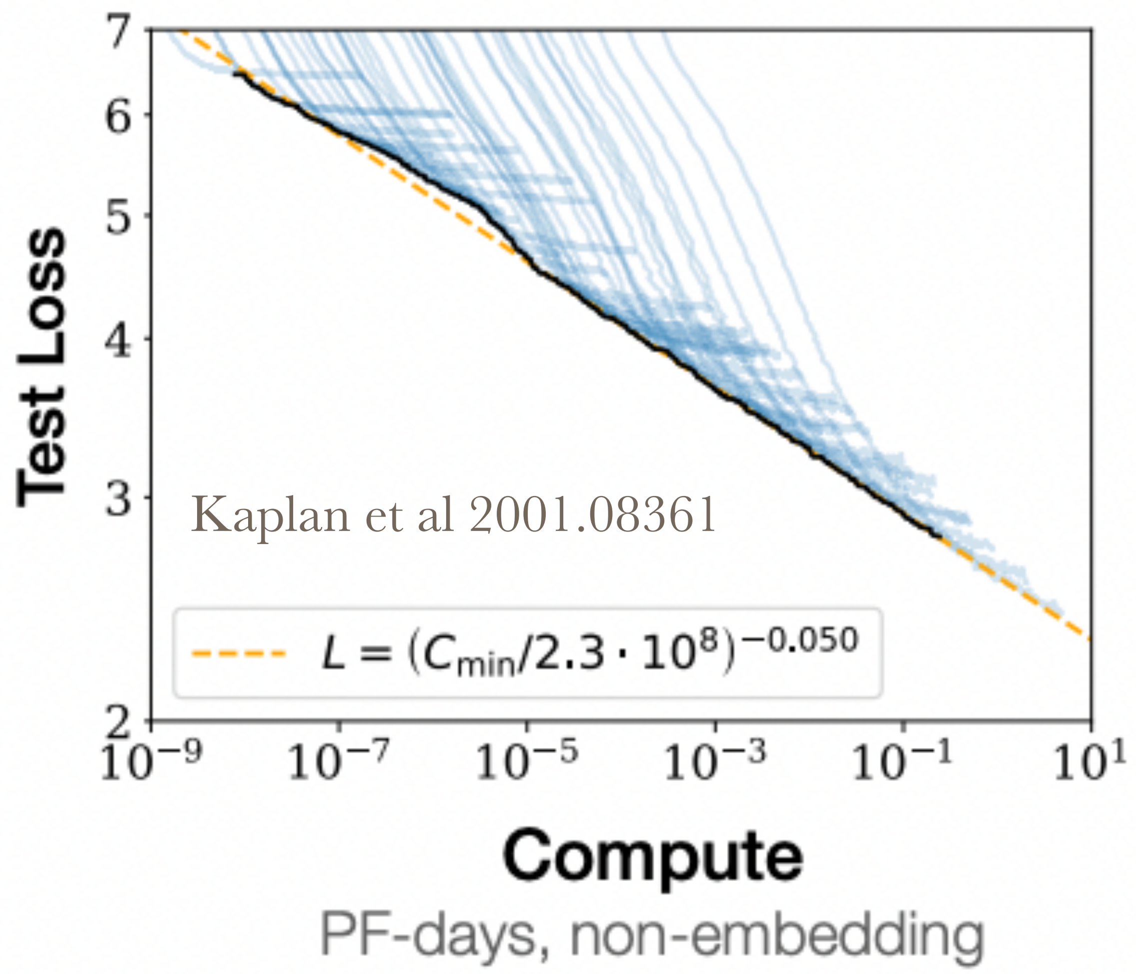
David Shih

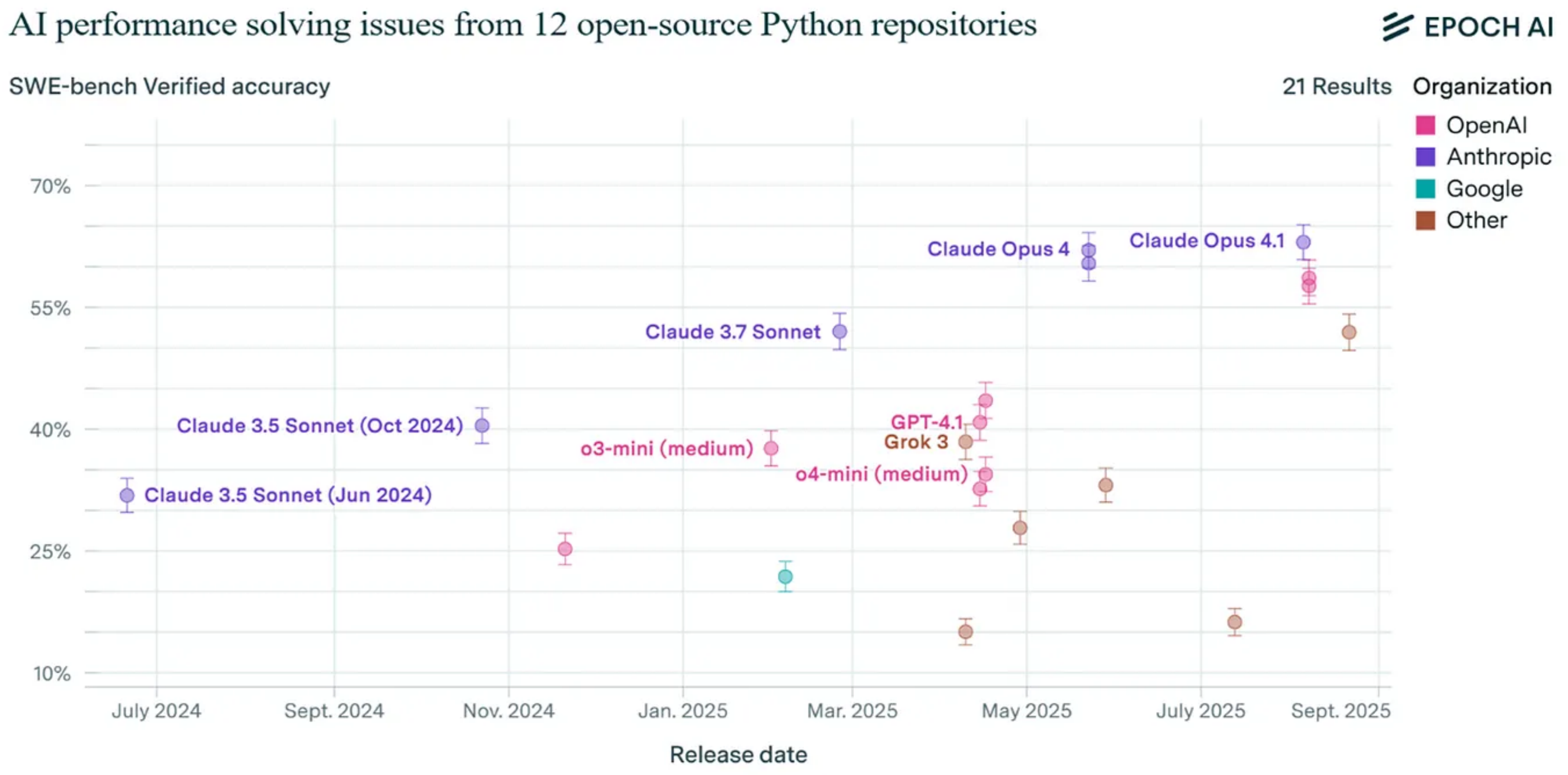
June 12, 2026

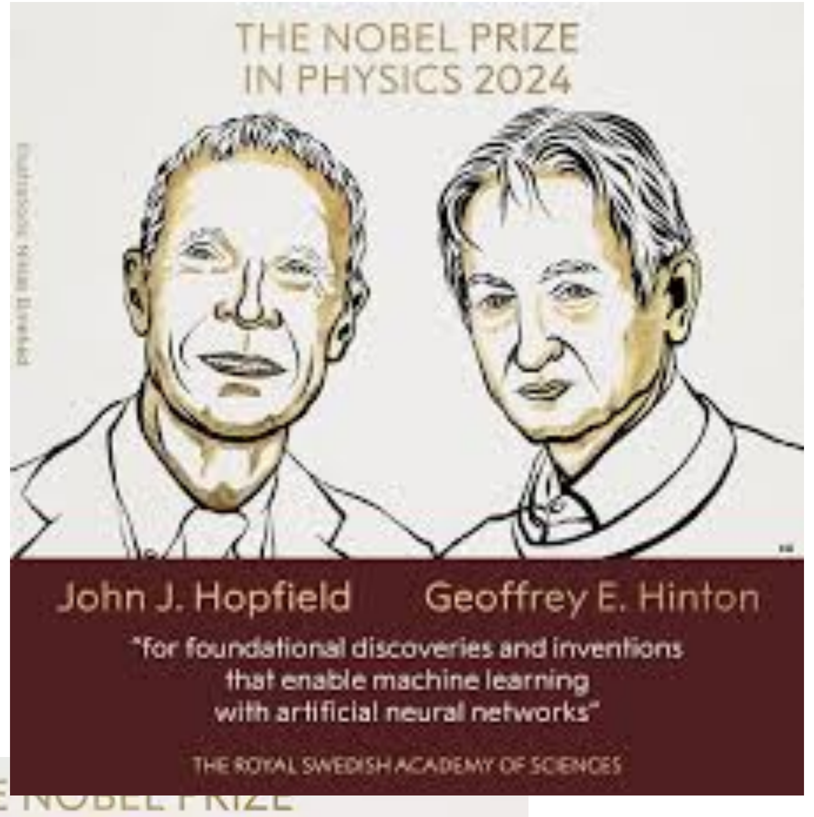
RUTGERS
THE STATE UNIVERSITY OF NEW JERSEY

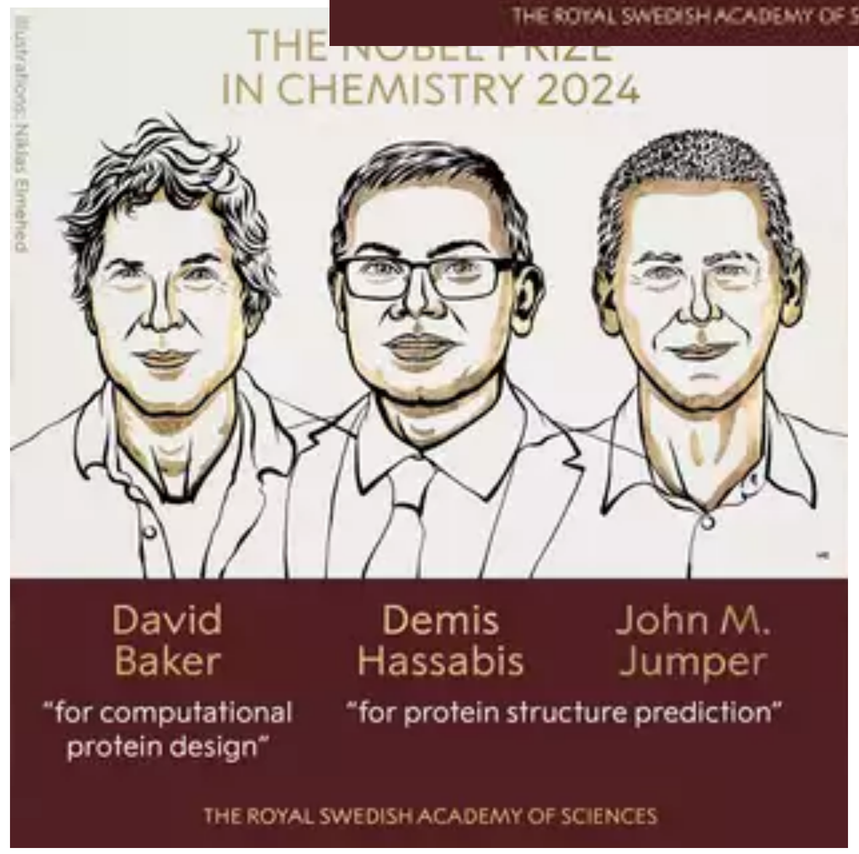
AI Revolution

We are witnessing a historic moment of technological advancement



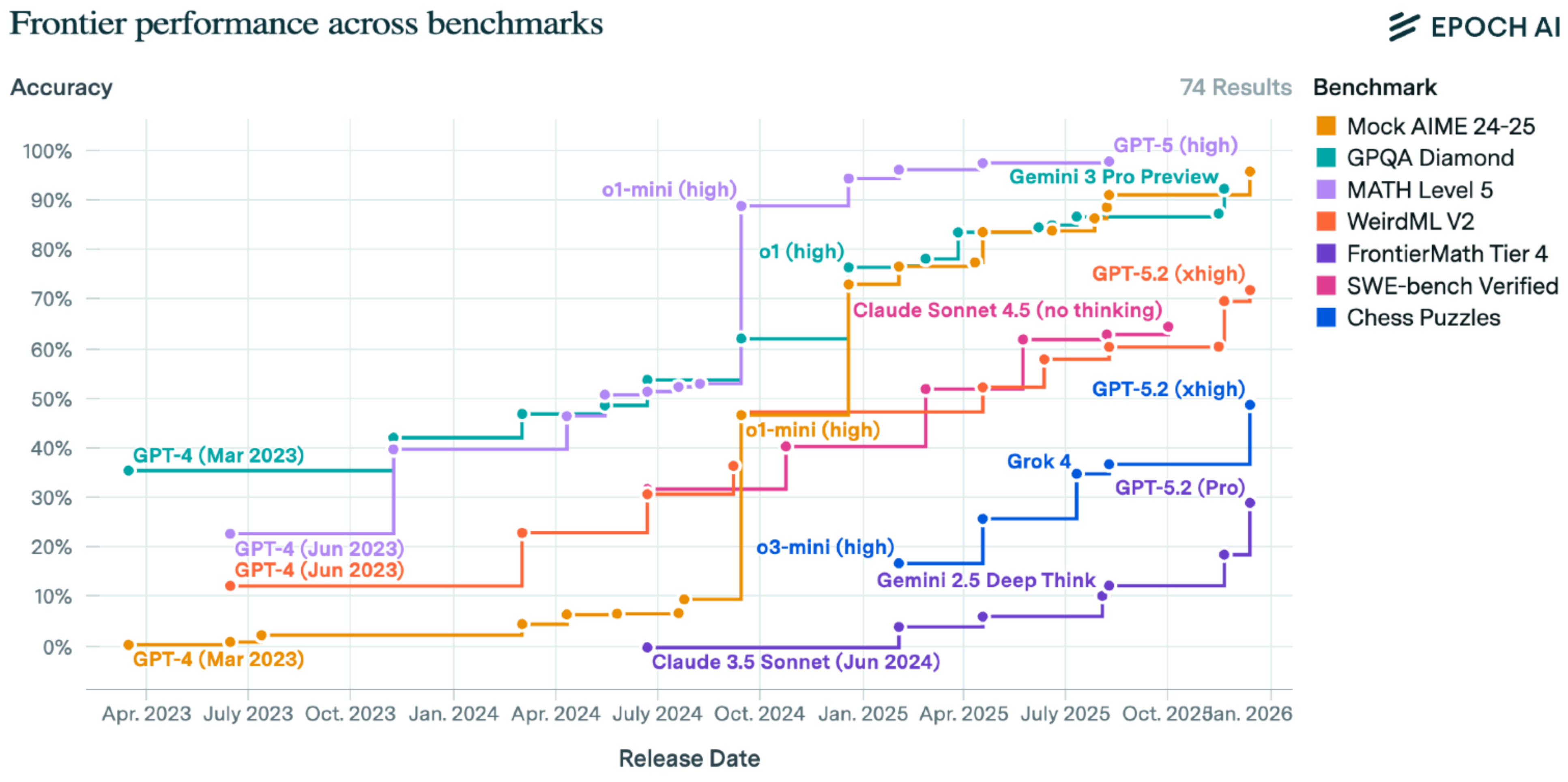






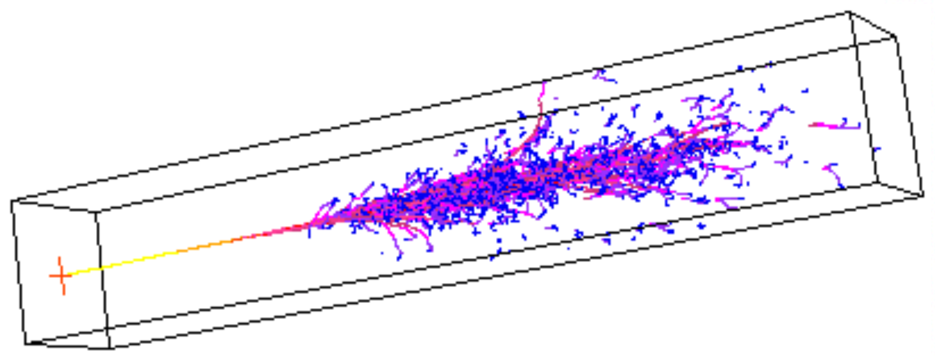
Google A.I. System Wins Gold Medal in International Math Olympiad

OpenAI said it, too, had built a system that achieved similar results.



epoch.ai

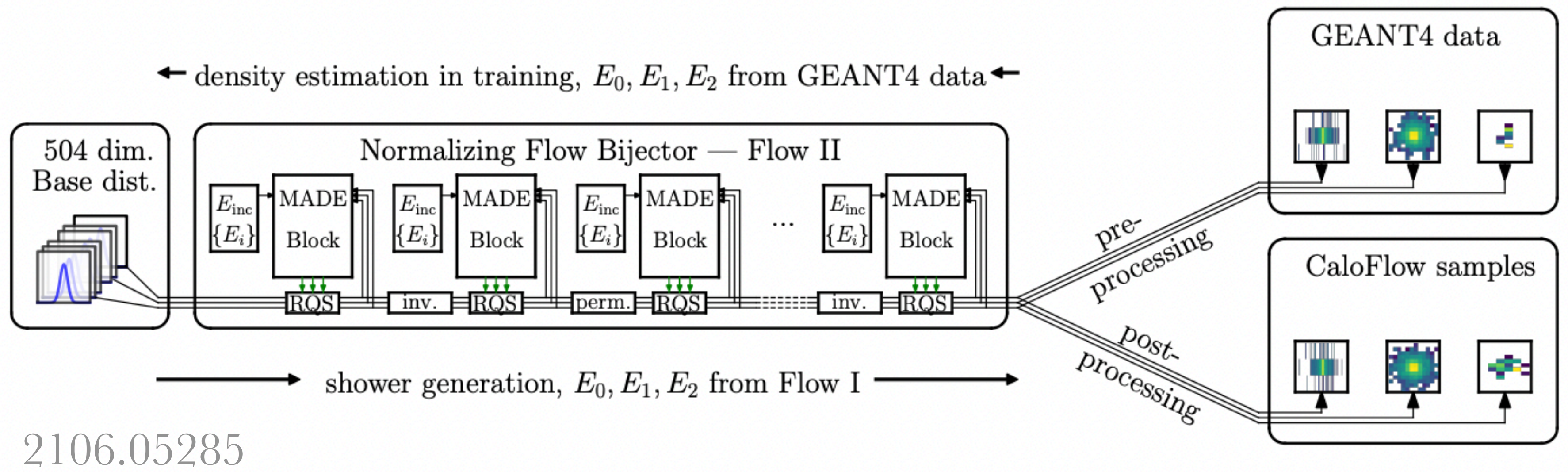
Fast simulation



CaloChallenge 2022: A Community Challenge for Fast Calorimeter Simulation

2410.21611

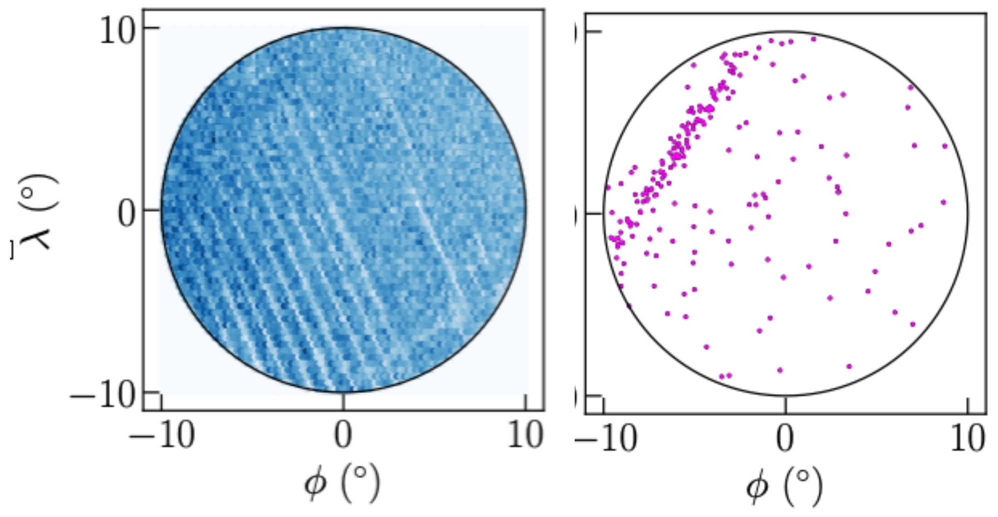
"Calorimeter Simulation", generated via midjourney, 2022

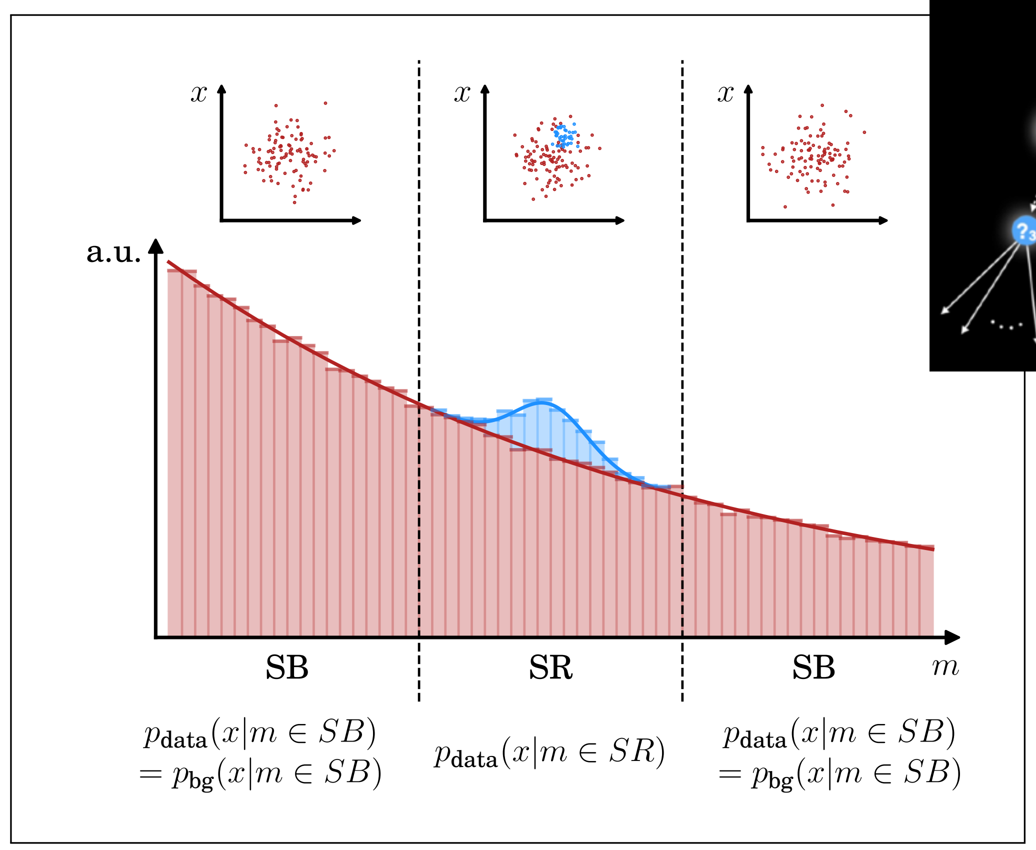


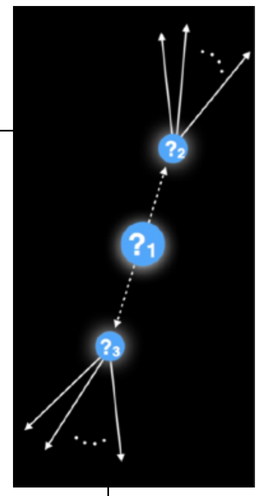
2106.05285

Anomaly Detection

2104.12789



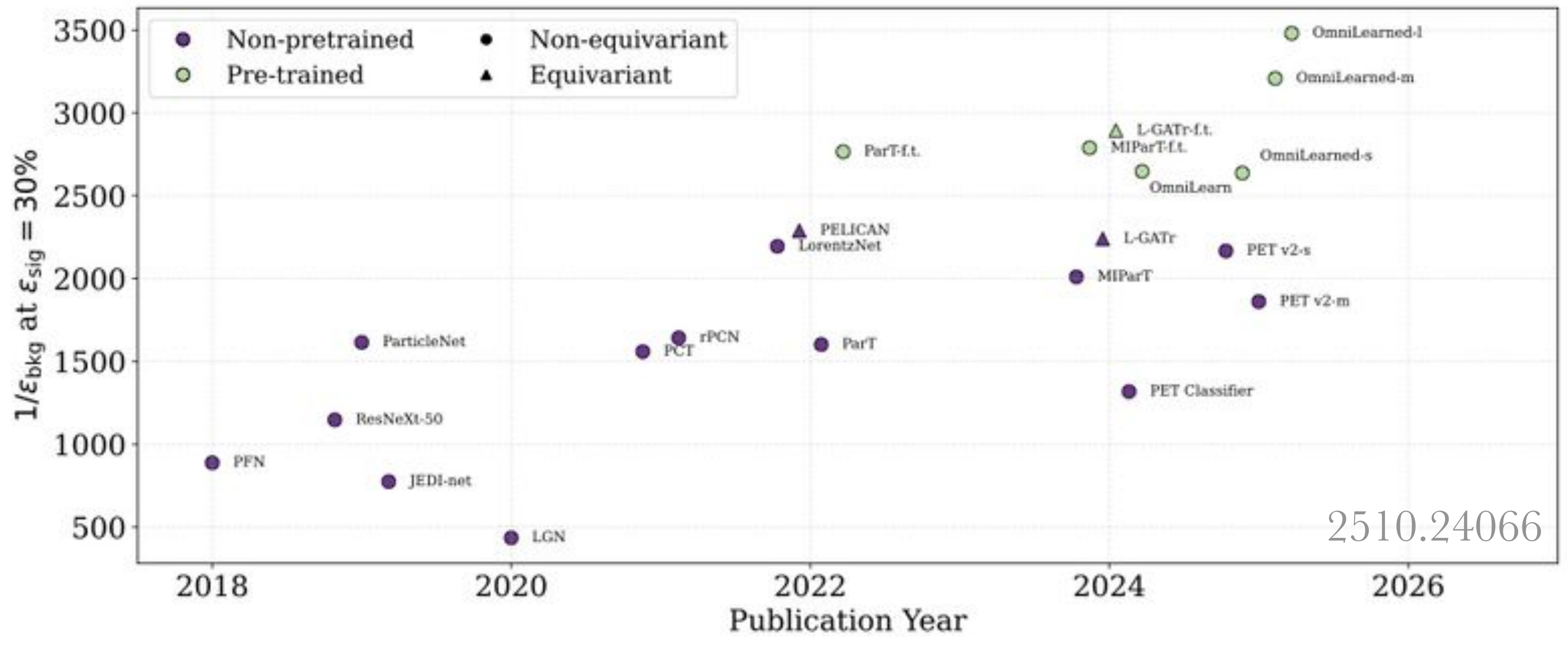




2109.00546

ML4HEP

Jet tagging



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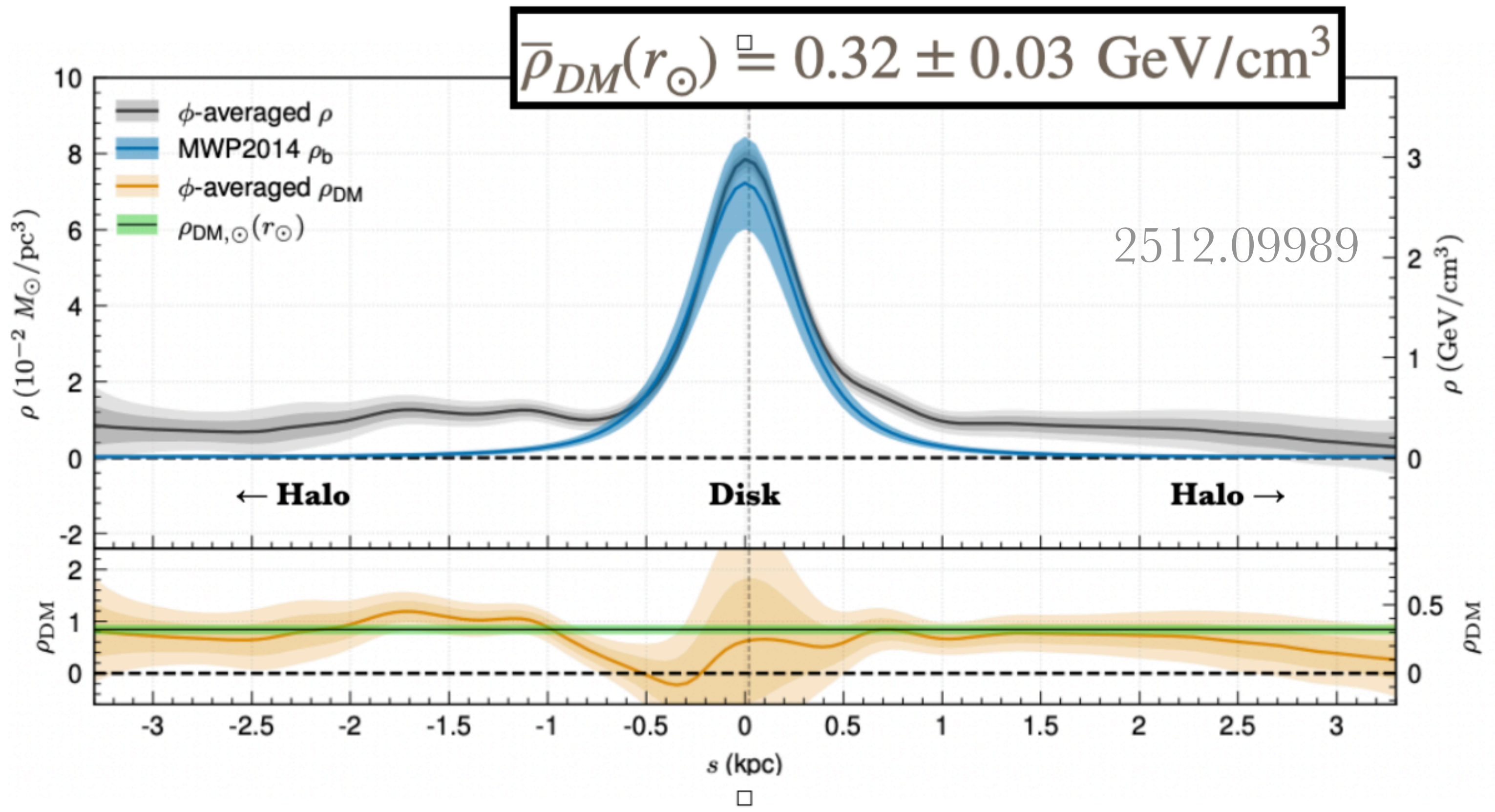
Novel measurements



2512.09989

And much, much more…

Agentic AI — a watershed moment

Claude Code, Codex — early 2025

Giving *agency* to LLMs — from question answering to reading/writing/executing code

BBC

Home News Sport Business Technology Health Culture Arts Travel Earth Audio Video Live

'Vibe coding' named word of the year by Collins Dictionary

tom's HARDWARE Follow

Claude-powered AI coding agent deletes entire company database in 9 seconds — backups zapped, after Cursor tool powered by Anthropic's Claude goes rogue

The New York Times

Artificial Intelligence › Apple Settlement Job Losses Meta Sued Vetting A.I. Models A.I. Spending Rec

SHOP TALK

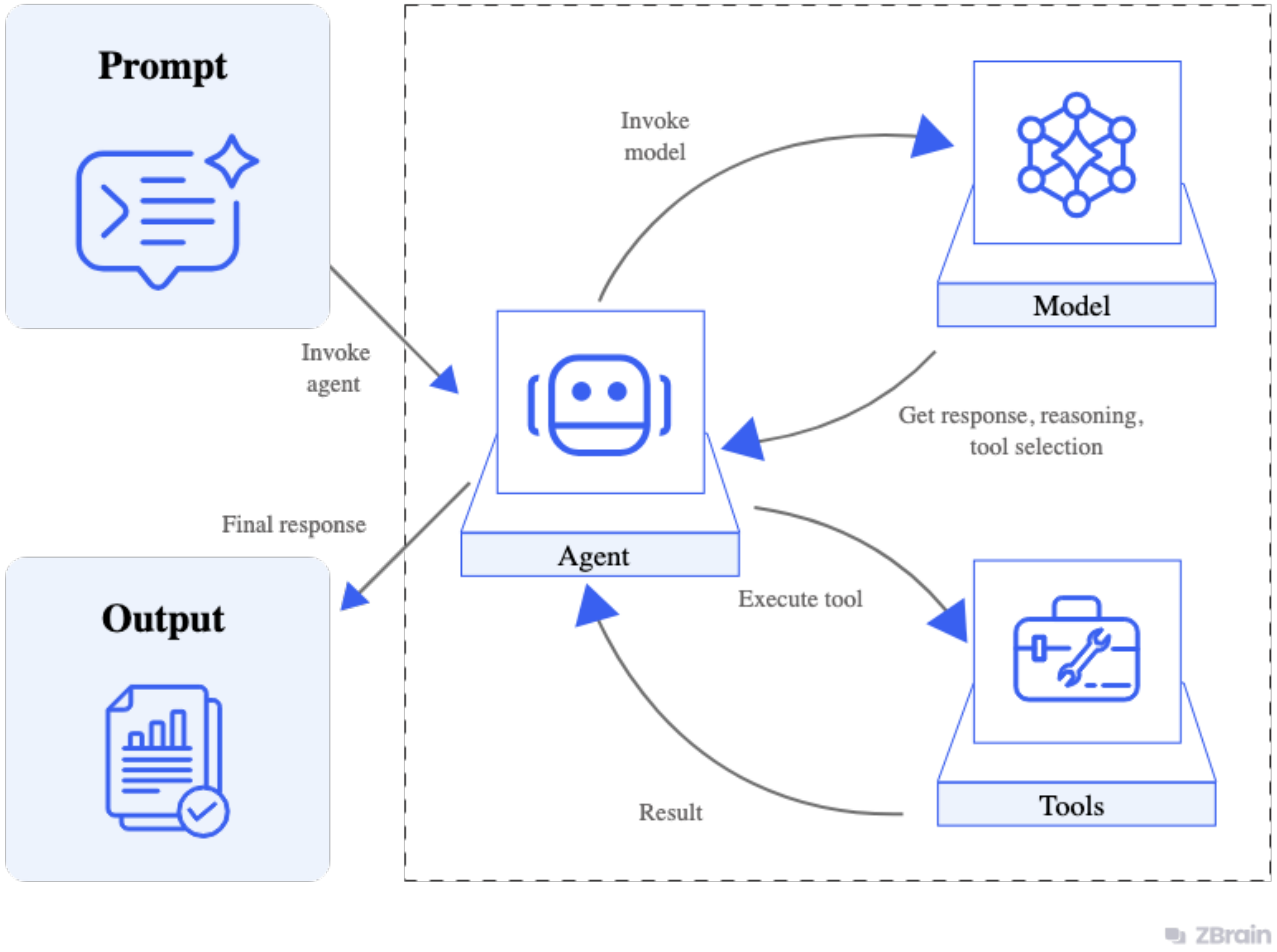
With 'Vibecoding,' A.I. Can Help Anyone Build an App

Bringing on artificial intelligence as a collaborator can make coding feel more accessible to those with little training in it, but there are trade-offs.

TECH

20,000 job cuts at Meta, Microsoft raise concern that AI-driven labor crisis is here

Agentic AI explained



- Agentic AI consists of
  - LLM backend (Claude, GPT, Gemini …)
  - a set of ***tools*** (bash, python, grep, text editor, …)
  - a ***harness/scaffold*** (traditional code infrastructure managing model responses and tool use)
- Examples include Claude Code, Codex, Antigravity, …

How are people using agentic AI?

- Particle physicists are exploring building custom harnesses for automating
  - anomaly detection
  - pheno tasks [ArgoLOOM, HEPTAPOD, MadAgents, CoLLM, FERMIACC, ColliderAgent/Magnus…]
  - experimental data analysis

Agents of Discovery

Sascha Diefenbacher[1], Anna Hallin[2],
Gregor Kasieczka[2], Michael Krämer[3], Anne Lauscher[4], Tim Lukas[2],

The FERMIACC: Agents for Particle Theory

Prateek Agrawal,[a] **Nathaniel Craig,**[a,b] **Amalia Madden,**[b] **and Iñigo Valenzuela Lombera**[a]
[a] *Department of Physics, University of California, Santa Barbara, CA 93106, USA*
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AI Agents Can Already Autonomously Perform Experimental High Energy Physics

Eric A. Moreno[∗†1,2], Samuel Bright-Thonney[∗‡1,2], Andrzej Novak[∗§1,2], Dolores Garcia[♯3], and Philip Harris[♭1,2]

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Increasing interest in rigorous benchmarking

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See: **CollIderBench** [2605.13950]
Faroughy, Palacios Schweitzer, Pang, Mishra-Sharma & DS

A new benchmark for agentic AI systems based on reinterpreting LHC searches ("recasting")

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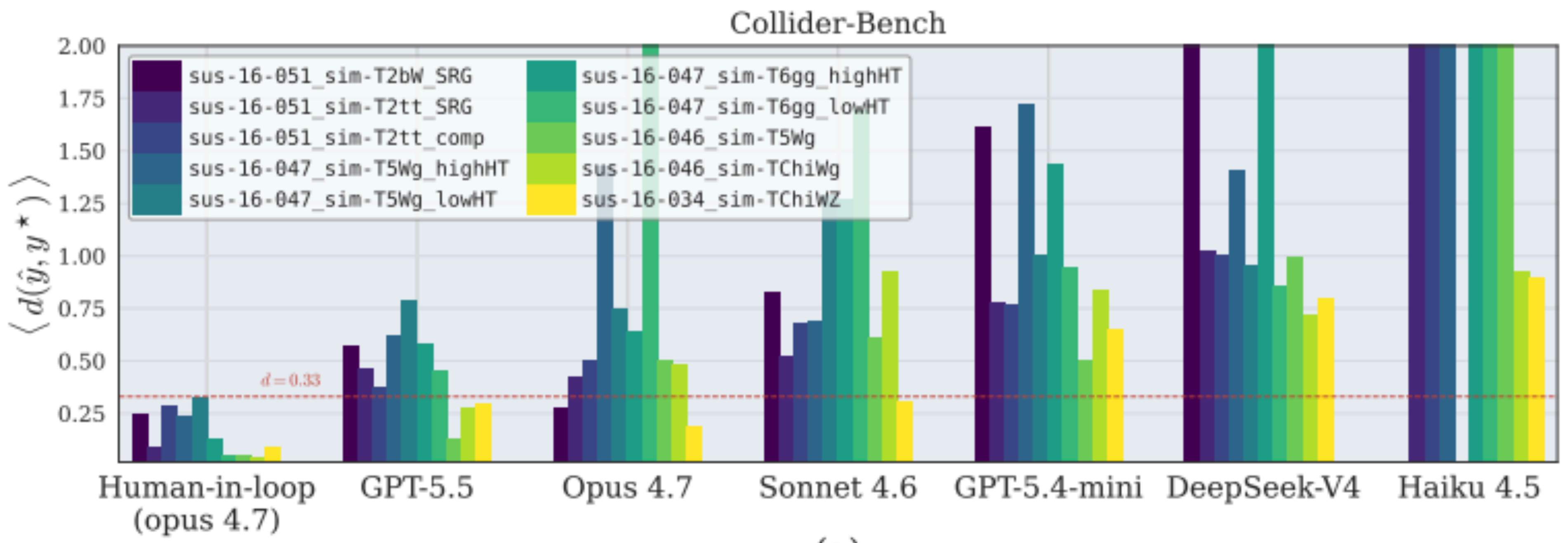
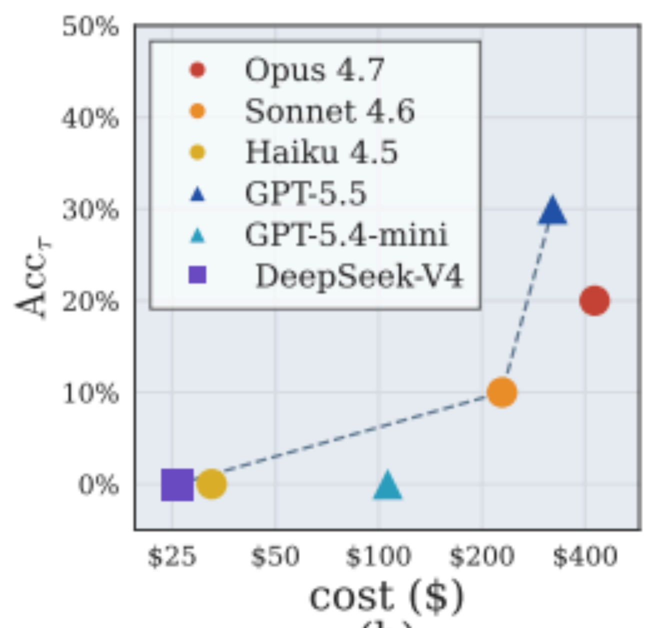


(a)



(b)

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As research assistants (~graduate student) — “vibe physics”

arXiv > hep-th > arXiv:2603.11164

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High Energy Physics - Theory

[Submitted on 11 Mar 2026 (v1), last revised 11 Apr 2026 (this version, v2)]

Learning to Unscramble: Simplifying Symbolic Expressions via Self-Supervised Oracle Trajectories

David Shih

We present a new self-supervised machine learning approach for symbolic simplification of complex mathematical expressions. Training data is generated by scrambling simple expressions and recording the inverse operations, creating oracle trajectories that provide both goal states and explicit paths to reach them. A permutation-equivariant, transformer-based policy network is then trained on this data step-wise to predict the oracle action given the input expression. We demonstrate this approach on two problems in high-energy physics: dilogarithm reduction and spinor-helicity scattering amplitude simplification. In both cases, our trained policy network achieves near perfect solve rates across a wide range of difficulty levels, substantially outperforming prior approaches based on reinforcement learning and end-to-end regression. When combined with contrastive grouping and beam search, our model achieves a 100\% full simplification rate on a representative selection of 5-point gluon tree-level amplitudes in Yang-Mills theory, including expressions with over 200 initial terms.

Comments: 14 pages, 6 figures, 2 tables; work done in collaboration with Claude Code; v2: refs added

arXiv > hep-ph > arXiv:2604.05034

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High Energy Physics - Phenomenology

[Submitted on 6 Apr 2026]

Learning to Unscramble Feynman Loop Integrals with SAILIR

David Shih

Integration-by-parts (IBP) reduction of Feynman integrals to master integrals is a key computational bottleneck in precision calculations in high-energy physics. Traditional approaches based on the Laporta algorithm require solving large systems of equations, leading to memory consumption that grows rapidly with integral complexity. We present SAILIR (Self-supervised AI for Loop Integral Reduction), a new machine learning approach in which a transformer-based classifier guides the reduction of integrals one step at a time in a fully online fashion. The classifier is trained in an entirely self-supervised manner on synthetic data generated by a scramble/unscramble procedure: known reduction identities are applied in reverse to build expressions of increasing complexity, and the classifier learns to undo these steps. When combined with beam search and a highly parallelized, asynchronous, single-episode reduction strategy, SAILIR can reduce integrals of arbitrarily high weight with bounded memory. We benchmark SAILIR on the two-loop triangle-box topology, comparing against the state-of-the-art IBP reduction code Kira across 16 integrals of varying complexity. While SAILIR is slower in wall-clock time, its per-worker memory consumption remains approximately flat regardless of integral complexity, in contrast to Kira whose memory grows rapidly with complexity. For the most complex integrals considered here, SAILIR uses only 40\% of the memory of Kira while achieving comparable reduction times. This demonstrates a fundamentally new paradigm for IBP reduction in which the memory bottleneck of Laporta-based approaches could be entirely overcome, potentially opening the door to precision calculations that are currently intractable.

Comments: 16 pages, 3 figures, 5 tables, work done in collaboration with Claude Code

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— branching out into new subfields

Approx 2 months of work

— compared to 6-12 months for a student

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see also Schwartz 2601.02484, Guevara et al 2602.12176, Zhang 2604.27050

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Outline

- Learning to unscramble: general framework
- **Application 1:** Dilog identities
- **Application 2:** Tree-level YM scattering amplitudes
- **Application 3:** IBP reduction of Feynman loop integrals
- Lessons learned

Learning to Unscramble: general framework

- Goal: ML methods for mathematical (symbolic) simplification

$$E_{complicated} = X_1 + X_2 + X_3 + X_4 + \dots$$

$$\Big\downarrow \quad \text{mathematical identities}$$

$$E_{simple} = Y_1$$

- Test beds: dilog sums, tree-level YM scattering amplitudes

(Dersy, Schwartz, Zhang 2206.04115; Cheung, Dersy, Schwartz 2408.04720)

Training data

- ML methods need training data
- **Key insight**: can think of complicated expressions as *scrambles* of simple ones by mathematical identities.
- Process of simplification is then *unscrambling.*

Dersy, Schwartz, Zhang 2206.04115

- *Strong analogy with Rubik's cubes!*
- Can cheaply create training data by applying random identities to simple expressions

$$E_{simple} \xrightarrow{\text{easy}} E_{complicated} \xrightarrow{\text{hard}} E_{simple}$$

Prior approaches: RL

Dersy, Schwartz, Zhang 2206.04115

MDP: Markov Decision Process
action classifier $\pi(a|s)$,
depends only on previous state

E_{simple} → $E_{complicated}$ → E_{simple}

random scrambles

RL agent (unsupervised MDP)

RL (PPO, TRPO) could not beat classical algorithm on even very simple simplification tasks (small dilog sums simplifying to zero).

Challenges: very sparse reward signal, non-monotonic reduction paths

Successful RL is very compute intensive and requires a lot of fine tuning.

Prior approaches: end-to-end regression

Cheung, Dersy, Schwartz 2408.04720

$$E_{simple} \xrightarrow{\text{random scrambles}} E_{complicated} \xrightarrow{\text{seq2seq translation}} E_{simple}$$

End-to-end regression with a seq2seq transformer achieved decent performance (80-90%) for dilog sums and scattering amplitudes

Drawback: mathematical correctness not guaranteed, transformer can hallucinate simpler but incorrect expressions!

Our approach: "Learning to Unscramble"

DS 2603.11164

Key insight: random scrambles can be reversed, step-by-step.

—> A wealth of simplification training data!!!

Idea from *ML for Rubik's cube literature*:
Takano 2106.03157

$$-\frac{\langle 1\,3\rangle[1\,4][2\,3]}{\langle 1\,2\rangle\langle 1\,4\rangle[1\,2]^2}$$

$$\Downarrow \quad \text{mom}^2\text{: } \langle 1\,3\rangle\,[3\,1] + \langle 1\,4\rangle\,[4\,1] + \langle 3\,4\rangle\,[4\,3] = 0$$

$$\frac{\langle 1\,4\rangle[1\,4]^2[2\,3] + \langle 3\,4\rangle[1\,4][2\,3][3\,4]}{\langle 1\,2\rangle\langle 1\,4\rangle[1\,2]^2[1\,3]}$$

$$\Downarrow \quad \text{mom}^2\text{: } \langle 1\,2\rangle\,[2\,1] - \langle 3\,4\rangle\,[4\,3] = 0$$

$$\frac{-\langle 1\,2\rangle[1\,2][1\,4][2\,3] + \langle 1\,4\rangle[1\,4]^2[2\,3] + 2\langle 3\,4\rangle[1\,4][2\,3][3\,4]}{\langle 1\,2\rangle\langle 1\,4\rangle[1\,2]^2[1\,3]}$$

$$\Downarrow \quad \text{Schouten: } [2\,4]\,[1\,3] + [2\,1]\,[3\,4] + [2\,3]\,[4\,1] = 0$$

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Our approach: "Learning to Unscramble"

DS 2603.11164

Key insight: random scrambles can be reversed, step-by-step.

—> A wealth of simplification training data!!!

Idea from *ML for Rubik's cube literature*:
Takano 2106.03157

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$$- 2\langle 3\,4\rangle[1\,2][2\,3][3\,4]^2 - \langle 1\,2\rangle[1\,2][1\,3][2\,3][2\,4] - 2\langle 1\,4\rangle[1\,2][1\,3][2\,4][3\,4] + 2\langle 3\,4\rangle[1\,3][2\,3][2\,4][3\,4]\Big)$$

Our approach: “Learning to Unscramble”

DS 2603.11164

$$E_{simple} \xrightarrow{\text{random scrambles}} E_{complicated} \xrightarrow{\textit{self-supervised}\ \text{MDP}} E_{simple}$$

Instead of unsupervised MDP of RL, train a ***self-supervised MDP*** on ***reversed random scramble sequences***

Learns to predict the best action from unscrambling steps

Addresses limitations of both previous approaches: highly dense reward signal and no hallucinations!

Application 1: Dilog sums

[DS 2603.11164]

$$\mathrm{Li}_2(x) = -\int_0^x dz\, \frac{\log(1-z)}{z}$$

$$(\textit{inversion}) \quad \mathrm{Li}_2(x) = -\mathrm{Li}_2\left(\frac{1}{x}\right) - \frac{\pi^2}{6} - \frac{\ln^2(-x)}{2}$$

$$(\textit{reflection}) \quad \mathrm{Li}_2(x) = -\mathrm{Li}_2(1-x) + \frac{\pi^2}{6} - \ln(x)\ln(1-x)$$

$$(\textit{duplication}) \quad \mathrm{Li}_2(x) = -\mathrm{Li}_2(-x) + \frac{1}{2}\mathrm{Li}_2(x^2)$$

- Toy version of Feynman loop integral simplification
- Class of expressions that Mathematica struggles to simplify

$$-4\,\mathrm{Li}_2\left(\tfrac{4}{x^2-8x+16}\right) + 8\,\mathrm{Li}_2\left(\tfrac{2}{x-4}\right) - 8\,\mathrm{Li}_2\left(\tfrac{2}{x-2}\right)$$

$$-6\,\mathrm{Li}_2\left(\tfrac{1}{x^2+2x}\right) - 6\,\mathrm{Li}_2\left(x^2+2x\right) + \tfrac{7}{2}\,\mathrm{Li}_2\left(\tfrac{4}{x^2-4x+4}\right)$$

$$-7\,\mathrm{Li}_2\left(\tfrac{x}{2}\right) - 7\,\mathrm{Li}_2\left(\tfrac{2}{x-2}\right)$$

$$-8\,\mathrm{Li}_2\left(\tfrac{x^2}{2x-2}\right) - 8\,\mathrm{Li}_2\left(-\tfrac{x^2}{2x-2}\right) - \tfrac{7}{2}\,\mathrm{Li}_2\left(\tfrac{4}{x^2+2x+1}\right)$$

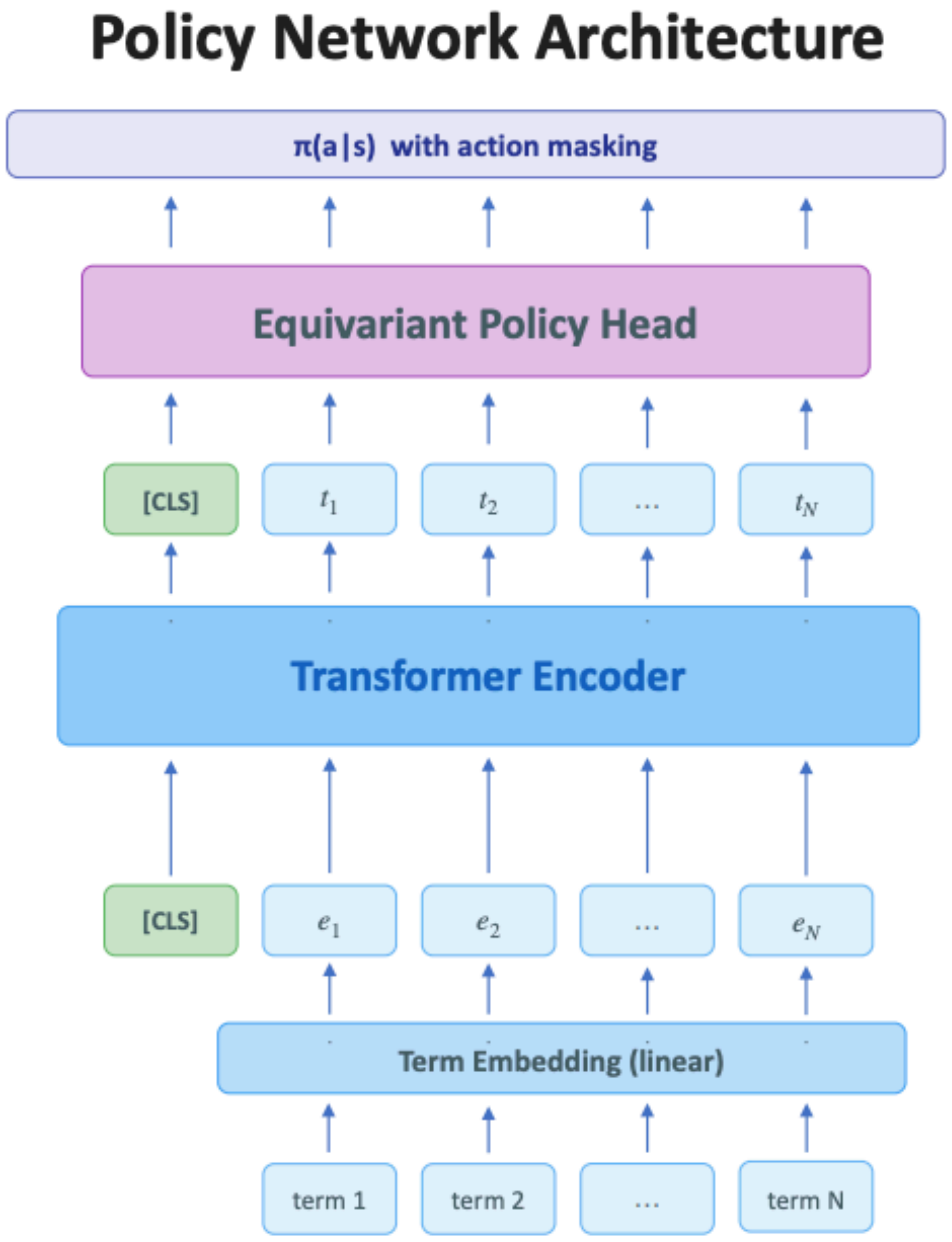
$$+4\,\mathrm{Li}_2\left(x^2+4x+4\right) + 4\,\mathrm{Li}_2\left(\tfrac{x^4}{4x^2-8x+4}\right) - 7\,\mathrm{Li}_2\left(-\tfrac{x}{2} - \tfrac{1}{2}\right)$$

$$-2\,\mathrm{Li}_2\left(\tfrac{1}{x+2}\right) + 8\,\mathrm{Li}_2\left(-\tfrac{1}{x+2}\right) - 10\,\mathrm{Li}_2(x+2)$$

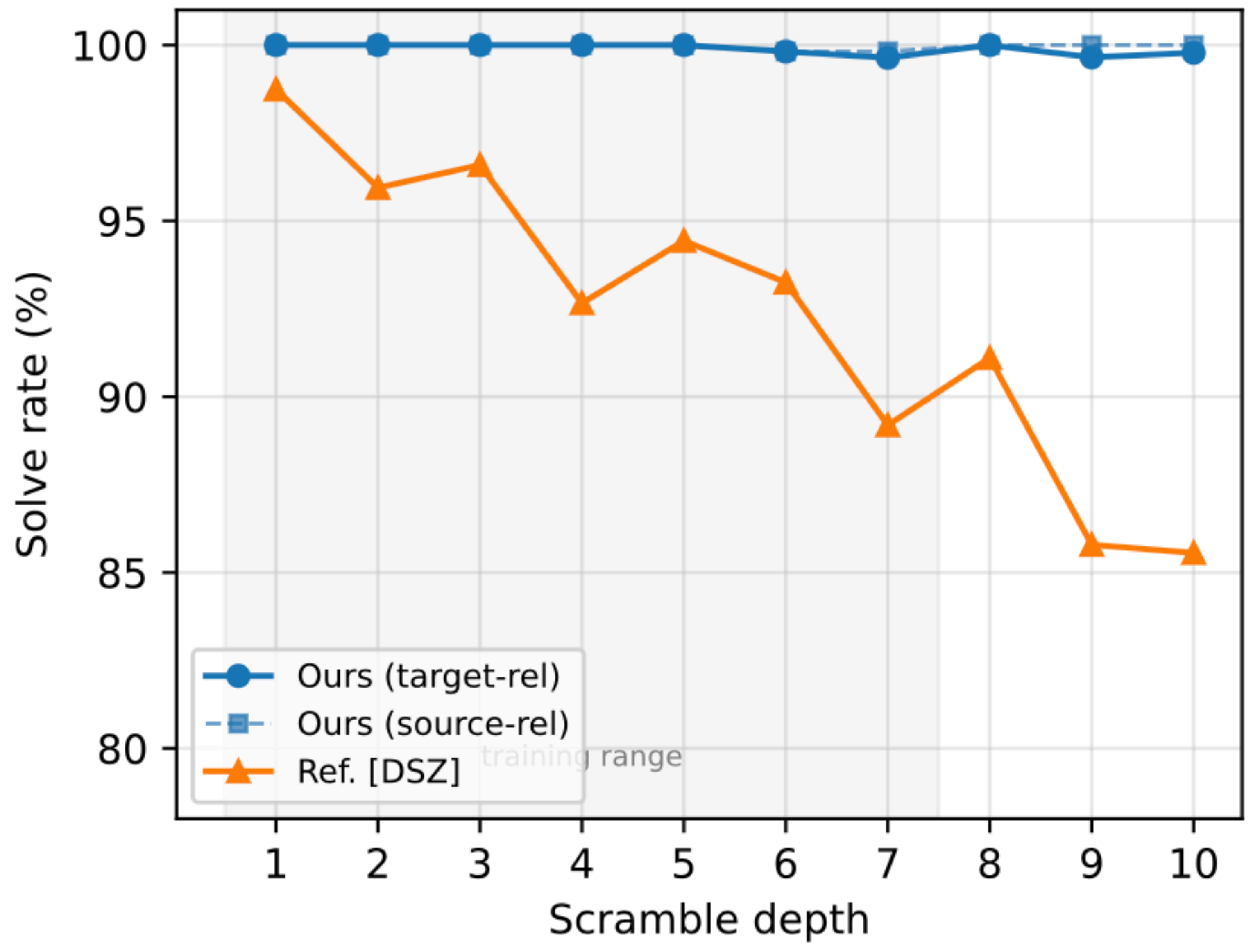
examples from Dersy, Schwartz, Zhang

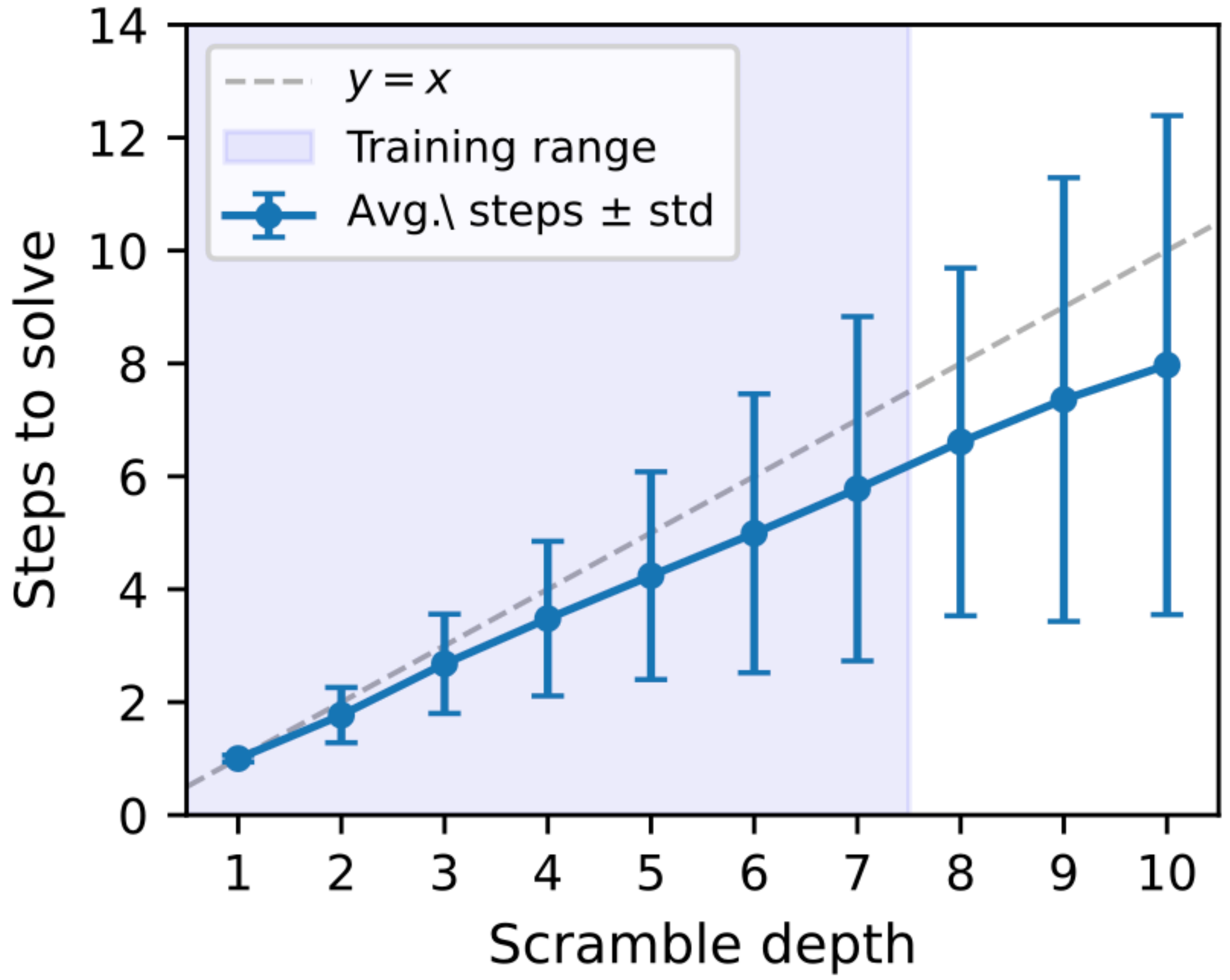
Learning to unscramble dilogs: setup

- Action space: (3 actions) x (up to 15 terms)
- Permutation-equivariant action classifier: 45 dimensional softmax (irrelevant actions masked)
- **Training data:** 100k samples scrambled from simple expressions -> 500k individual unscramble steps
- **Test data:** 5k expressions from DSZ



Learning to unscramble dilogs





- Nearly 100% simplification rate! Much better than end-to-end transformer (DSZ)
- Only 6 failures out of 5k test set. (Only 2 if we demand some simplification)
- Excellent performance generalizes beyond training set!
- Finds *shorter* simplification paths than training data on average

Application 2: scattering amplitudes

[DS 2603.11164]

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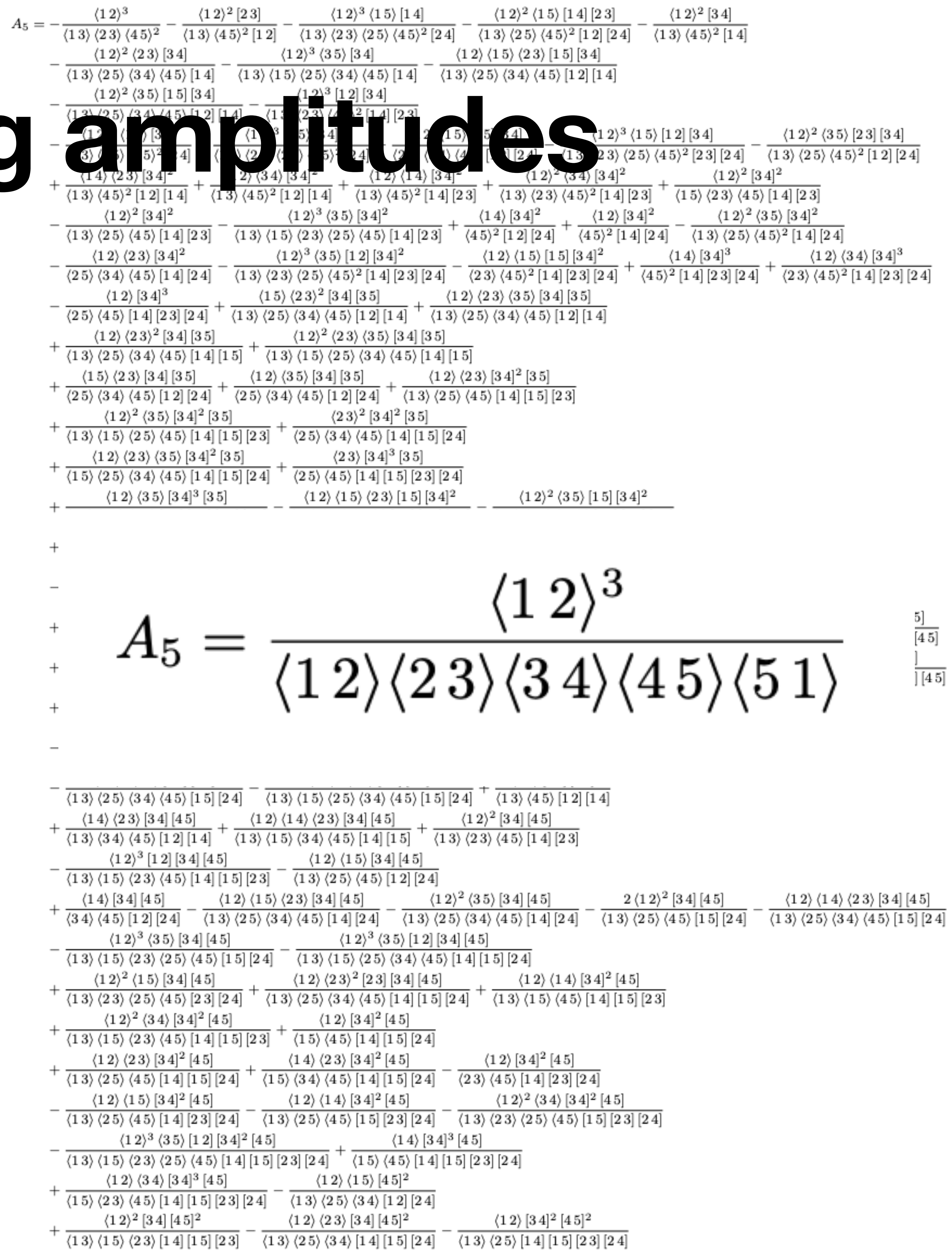


$$A_5 = \frac{\langle 1\,2\rangle^3}{\langle 1\,2\rangle\langle 2\,3\rangle\langle 3\,4\rangle\langle 4\,5\rangle\langle 5\,1\rangle}$$

Application 2: scattering amplitudes

[DS 2603.11164]

- Example of 5pt YM tree amplitude computed with Feynman diagrams
  (from Cheung, Dersy, Schwartz)

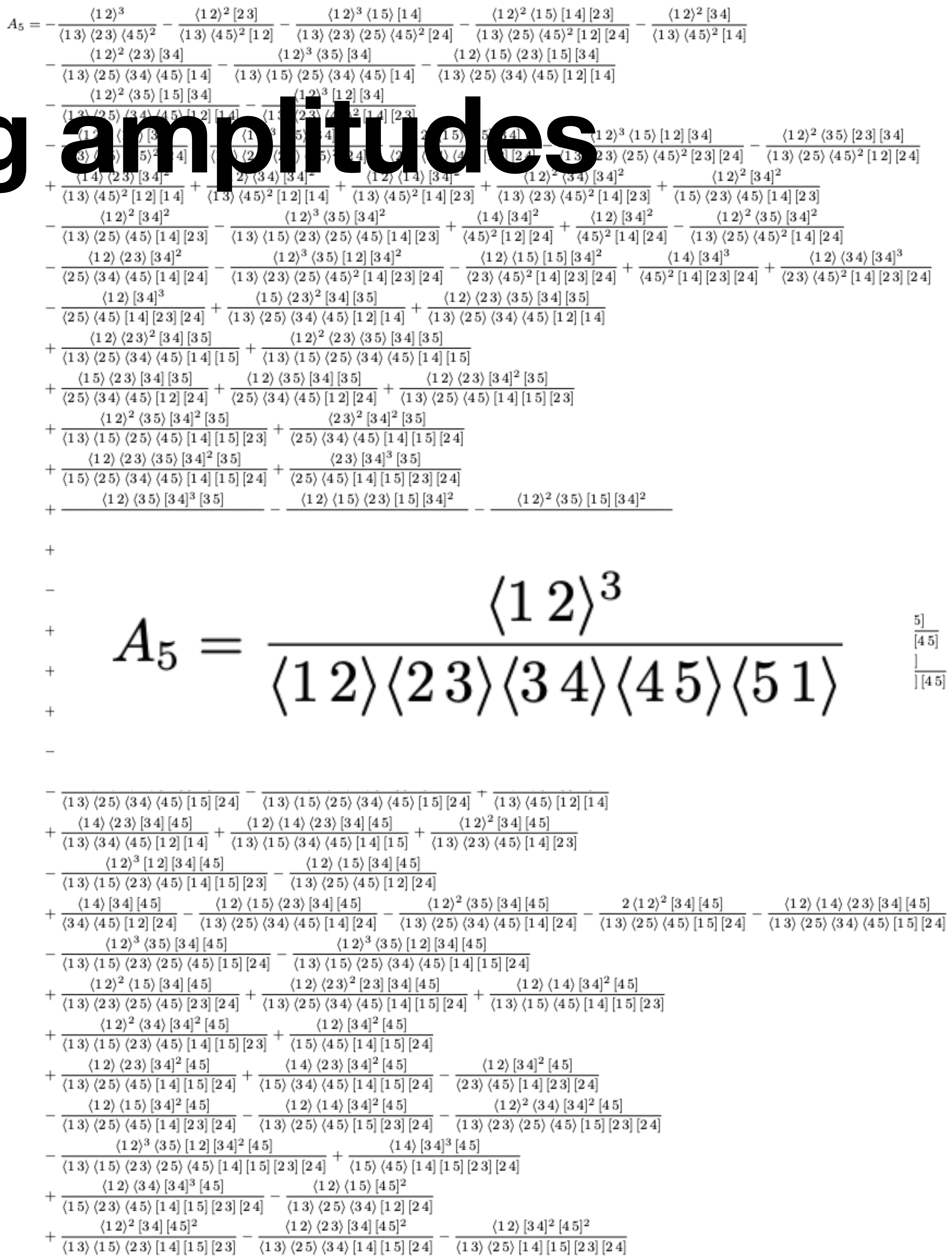
- Known to simplify to **Parke-Taylor amplitude**

- through repeated application of identities:

$$\text{Schouten identity}: \begin{cases} \langle ij\rangle\langle kl\rangle = \langle il\rangle\langle kj\rangle + \langle ik\rangle\langle jl\rangle \\ [ij][kl] = [il][kj] + [ik][jl] \end{cases}$$

$$\text{momentum squared}: \sum_{\substack{i<j \\ (i,j)\in S_1^n}} \langle ij\rangle[ji] = \sum_{\substack{k<l \\ (k,l)\in S_2^n}} \langle kl\rangle[lk]$$

$$\text{momentum conservation}: \sum_{j=1}^{n} \langle ij\rangle[jk] = 0 \quad \forall i, k$$



$$A_5 = \frac{\langle 1\,2\rangle^3}{\langle 1\,2\rangle\langle 2\,3\rangle\langle 3\,4\rangle\langle 4\,5\rangle\langle 5\,1\rangle}$$

Scattering amplitudes: setup

- Start from 1-3 terms (shared denominator, same mass dimension and little-group scaling)
- Scramble with identities; also multiplication by unity and addition by zero
  - Total action space: ~1.4k for 4 pts, ~4k for 5 pts and ~30k for 6 pts

$$\mathcal{M} \to \mathcal{M}\frac{\langle 12\rangle}{\langle 12\rangle} \to \mathcal{M}\frac{\langle 13\rangle\langle 25\rangle - \langle 15\rangle\langle 23\rangle}{\langle 12\rangle\langle 35\rangle}$$

$$\mathcal{M} + \frac{[34]-[34]}{\mathcal{D}}\mathcal{F} \to \mathcal{M} + \frac{[14][35]-[13][45]-[15][34]}{\mathcal{D}[15]}\mathcal{F}$$

Training data

500k scramble trajectories.
—> ~1M single steps
(per n-pt).

Test data

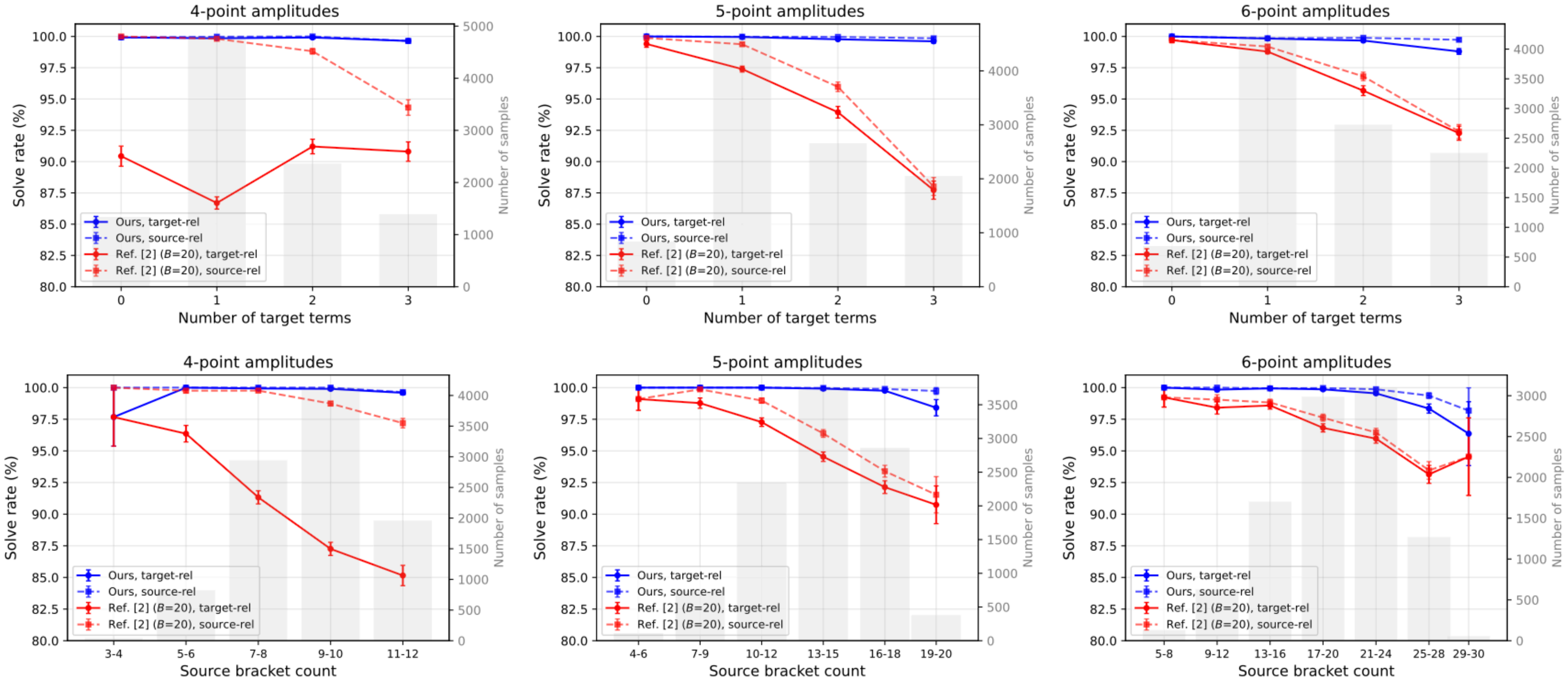
10k test expressions from CDS enabling head-to-head comparison.

Additional test data

100 actual 5pt YM amplitudes
(all simplifying down to PT form)

Scattering amplitudes: results

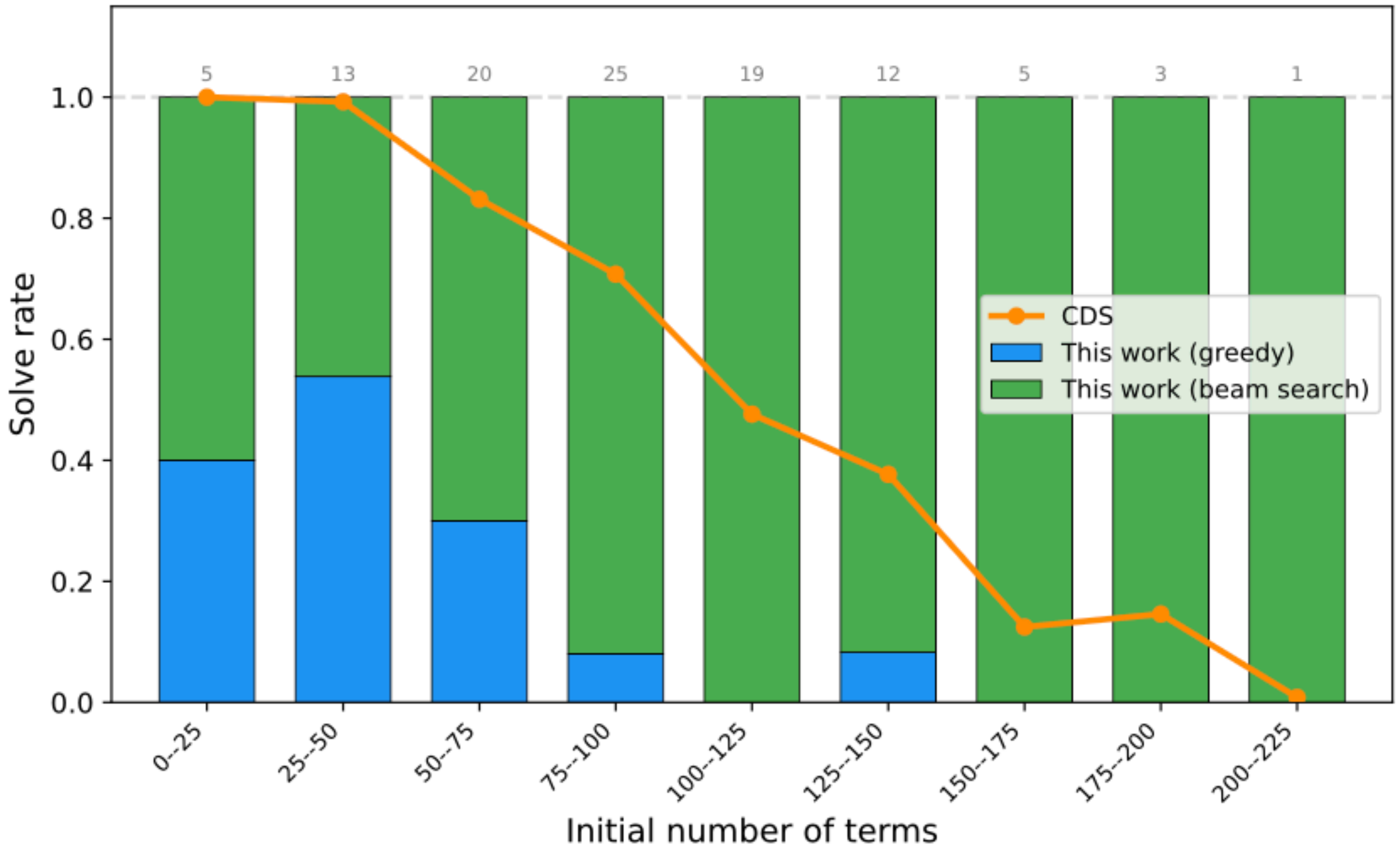
Target relative: simplifies completely to target
Source relative: simplifies source any amount



- We achieve nearly perfect simplification rate across all target and source complexities
- Again, big improvement vs the end-to-end transformer of CDS

Scattering amplitudes: results

- We also achieved 100% simplification of actual 5pt YM amplitudes (up to ~200 initial terms), another big improvement over CDS!



Application 3: IBP reduction

[DS 2604.05034]

- At the precision frontier, calculation of SM processes with Feynman diagrams can generate hundreds of loop integrals. These need to be reduced before numerically evaluating.
- Integration-by-parts identities are linear relations among loop integrals, parametrized by *seed* $\mathbf{a}$ and *operation* (choice of loop momentum k_i and additional momentum v^μ):

$$I[\mathbf{a}] = \int \prod_{j=1}^{L} d^d k_j \prod_{i=1}^{N_p+N_s} \frac{1}{D_i^{a_i}} \qquad \int \prod_{j=1}^{L} d^d k_j \frac{\partial}{\partial k_i^\mu} \left(v^\mu \cdot \text{integrand}\right) = 0,$$

- Can use IBP identities to reduce any loop integral to a basis of master integrals

Laporta algorithm

r: total denominator (propagator) weight

$$w(I[\mathbf{a}]) = \left(\sum_i \max(a_i, 0), \ \sum_i |\min(a_i, 0)|, \ \mathbf{w}_3 \right)$$

s: total numerator weight

- Basis for general purpose IBP reduction programs like **`Kira`**
    - Make a giant linear system of IBPs
    - Use Gaussian elimination to target highest weight IBP
    - Continue until fully reduced to master integrals

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1k} \\ a_{21} & a_{22} & \cdots & a_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ a_{k1} & a_{k2} & \cdots & a_{kk} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_k \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix},$$

$$\left[\begin{array}{cccc|c} a'_{11} & a'_{12} & \cdots & a'_{1k} & b'_1 \\ 0 & a'_{22} & \cdots & a'_{2k} & b'_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & a'_{kk} & b'_k \end{array}\right].$$

- Guaranteed to work: number of IBP identities grows faster than the number of seeds
- But very computationally inefficient — **memory wall**

<u>S</u>elf-supervised <u>AI</u> for <u>L</u>oop <u>I</u>ntegral <u>R</u>eduction (SAILIR)

- Learning to Unscramble applied to IBP reduction
- Some challenges unique to IBP reduction:
  - weight reduction instead of term reduction
  - much bigger action space (number of IBPs combinatorially large)
    - but set of valid actions much smaller (10-100 per expression) but variable (depends on expression)
  - much more elaborate inference

Weight vs term reduction

- Weight reodering:
  - to train the MDP to reduce by weight, we reorder the unscrambles to monotonically reduce highest weight integral in the expression at each step (can prove that this can always be done)
- Sector-wise reduction:
  - Loop integrals labeled by indices $\mathbf{a} = (a_1, a_2, \ldots)$ organize into sectors — which propagator factors are present
  - Notion of subsectors

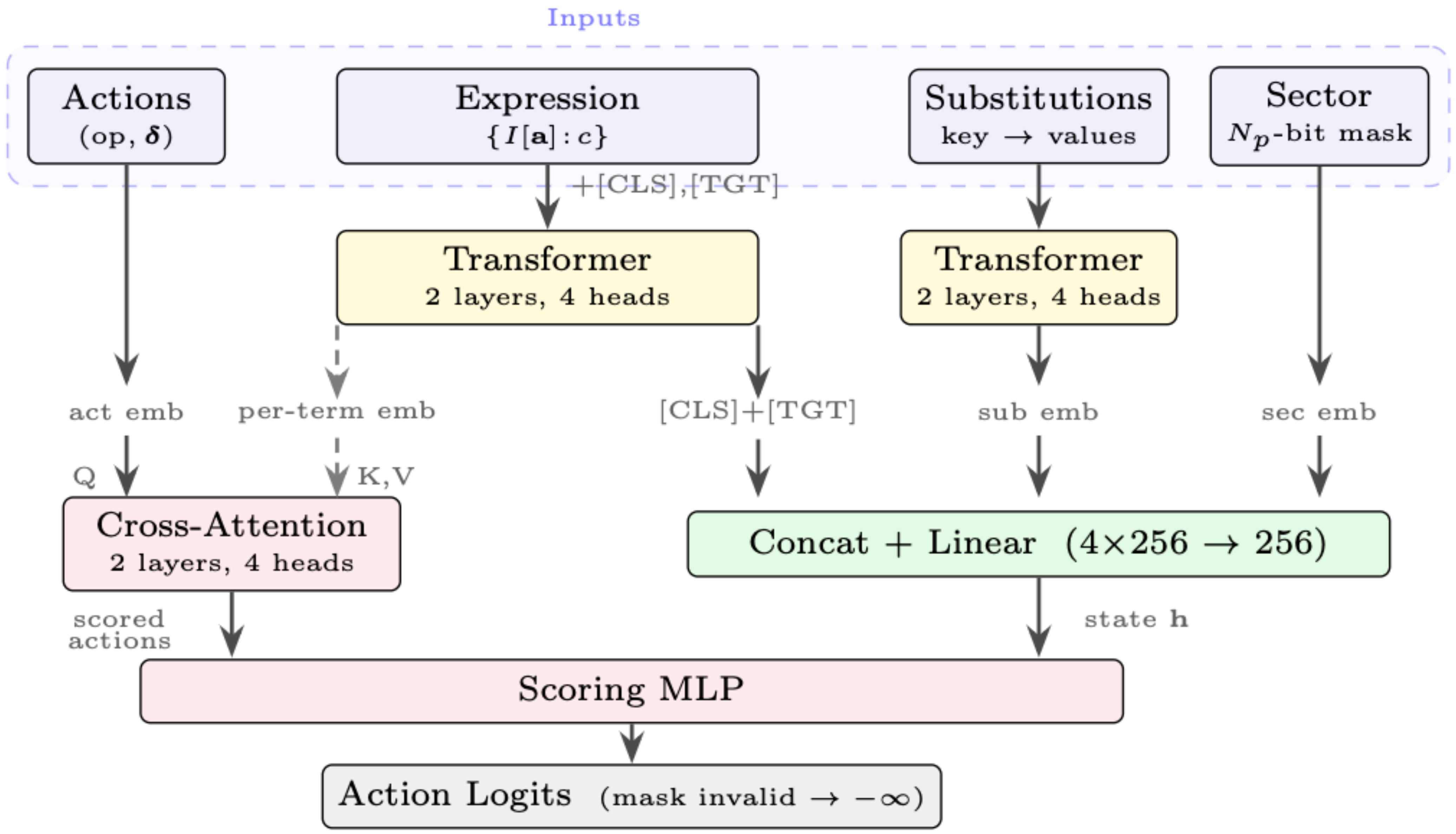
$$(2,1,-1,1) \rightarrow (1,1,0,1)$$

$$(-1,0,-1,3) \rightarrow (0,0,0,1)$$

  - Laporta reduction can work sectorwise: reduce to **corner integral** I[1,1,0,1], I[0,0,0,1], etc — modulo subsectors

Variable action space: learning to rank

- Used in information retrieval (ML for search engines)
  - Expression <-> question
  - actions <-> potential answers that we want to rank



- Use cross attention between encoded actions and expression to produce a per-action score
- Softmax gives classifier over all valid actions

Inference engineering

- For dilogs and scattering amplitudes, “greedy” action selection:

$$a_n = \text{argmax } \pi(a \mid s_n)$$

  was sufficient to reduce the randomly-scrambled held-out test data

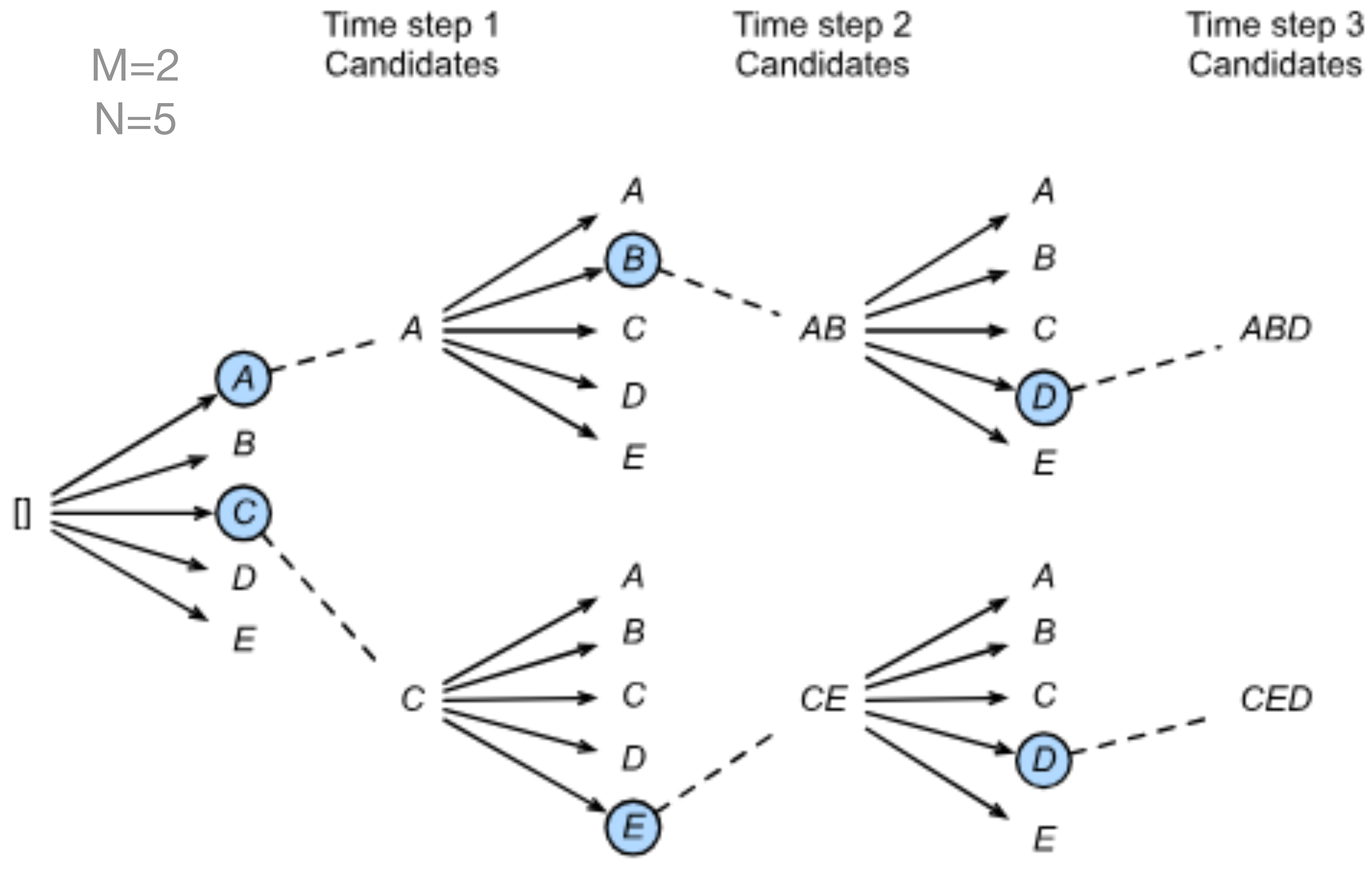
- But for IBP reduction, the train/test mismatch meant more sophisticated methods were required.

Train: sum of higher weight integrals -> single corner integral eg I[1,1,0,1,1]

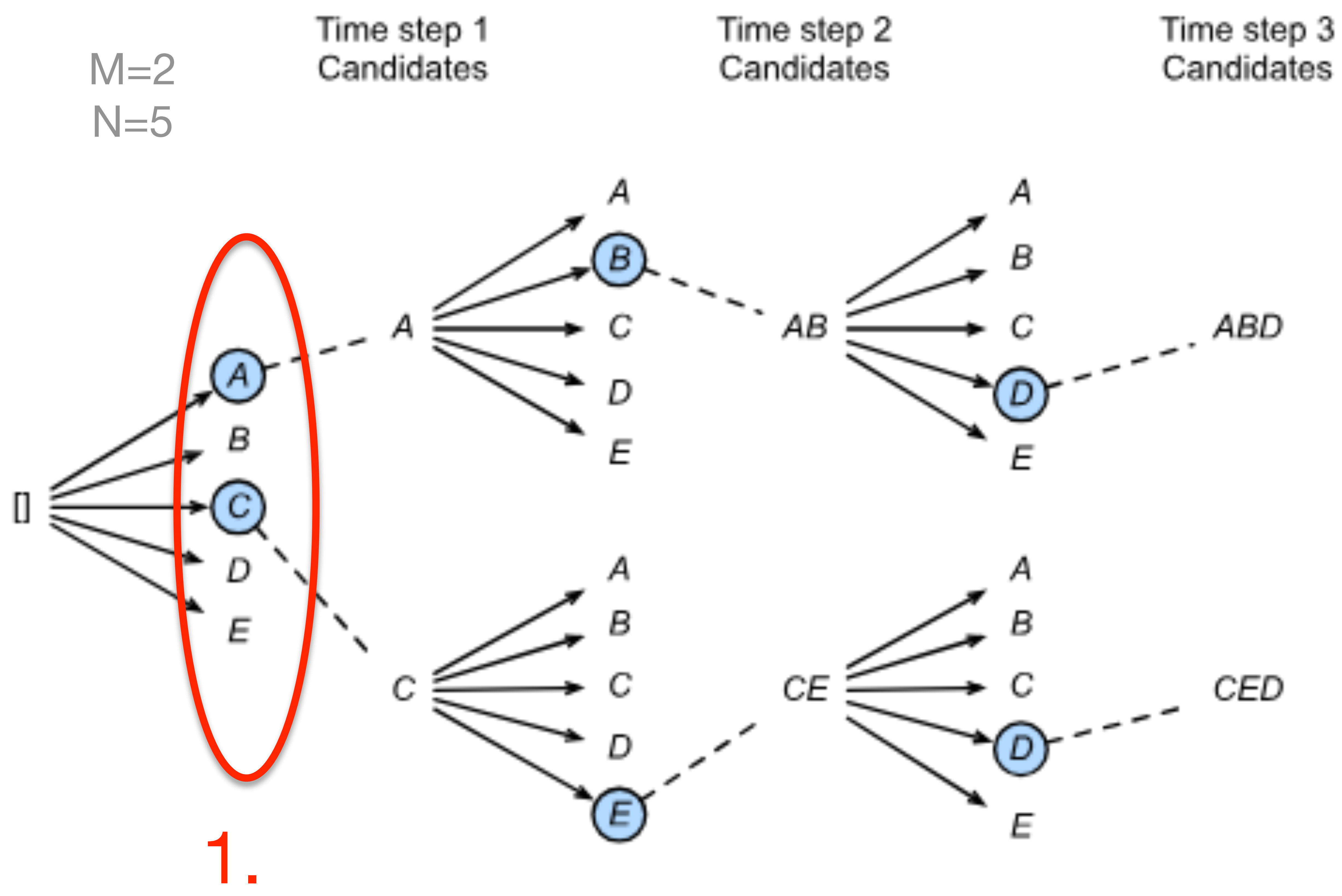
Test: single high weight integral eg I[3,4,-2,2,2] -> sum of corner integrals

Inference engineering: beam search

M=2
N=5

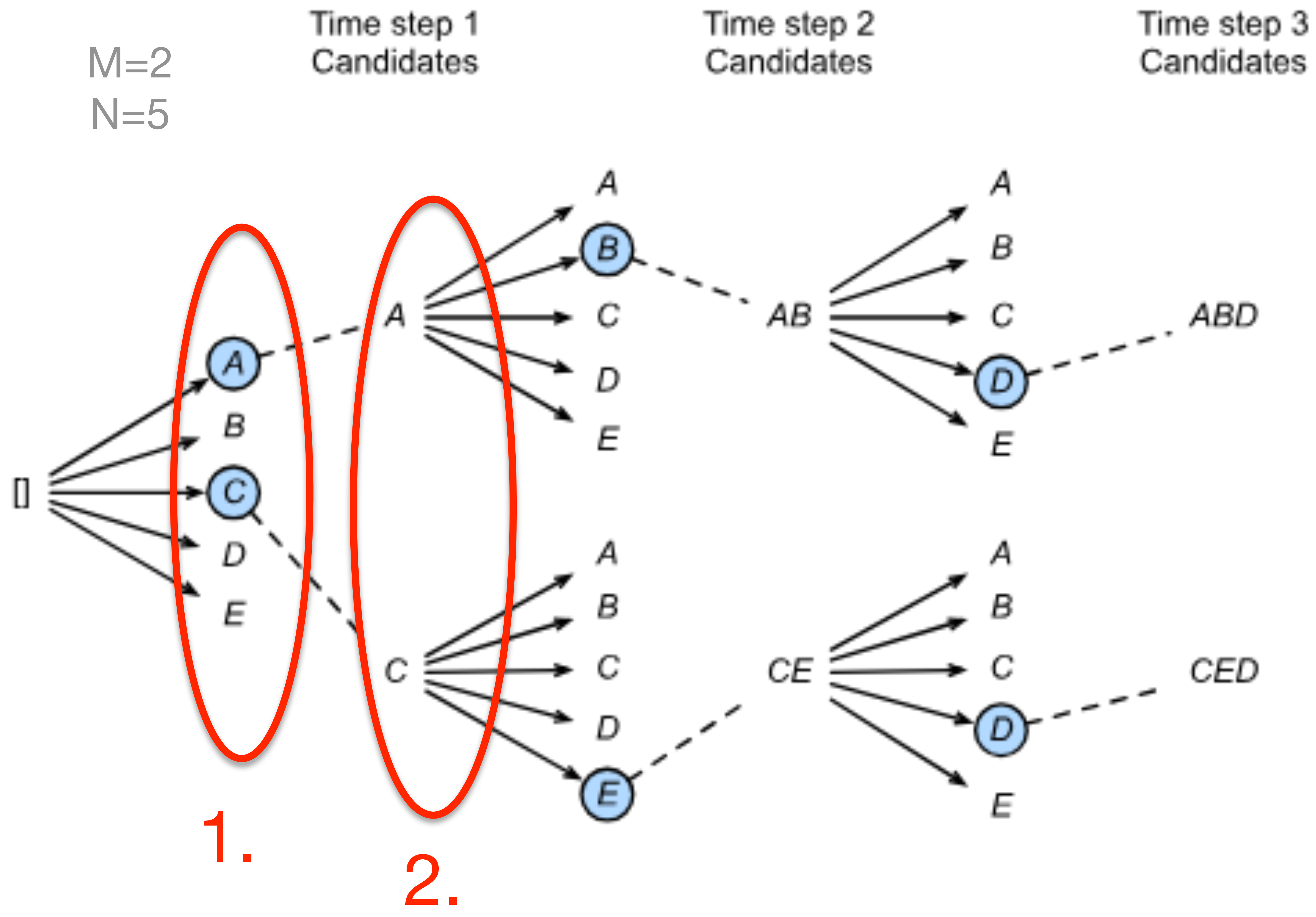


Inference engineering: beam search



1. Maintain a "beam" of M(=20) promising expressions.

Inference engineering: beam search



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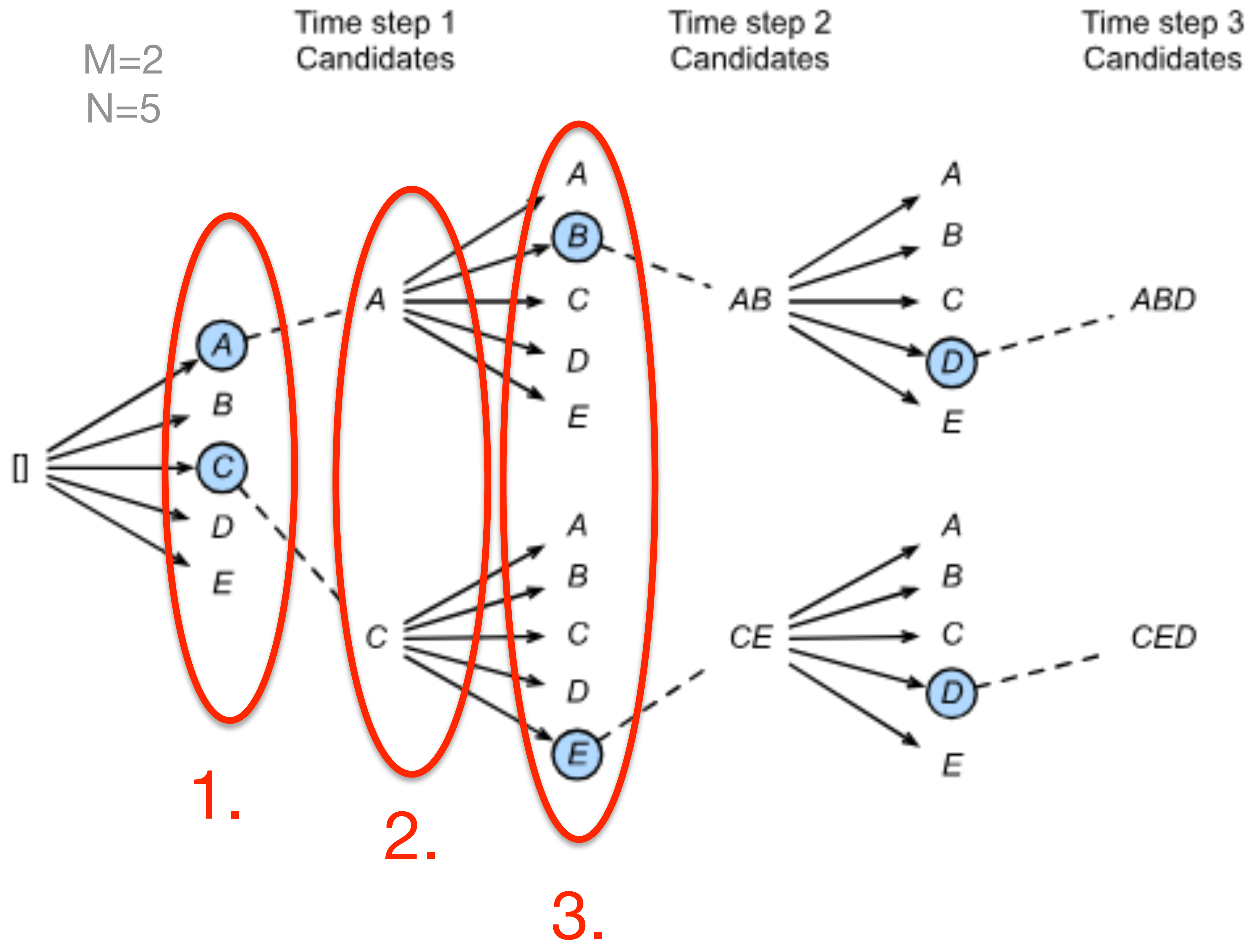
2. For each expression, act with the N(=20) top ranked actions according to the action classifier.

Inference engineering: beam search



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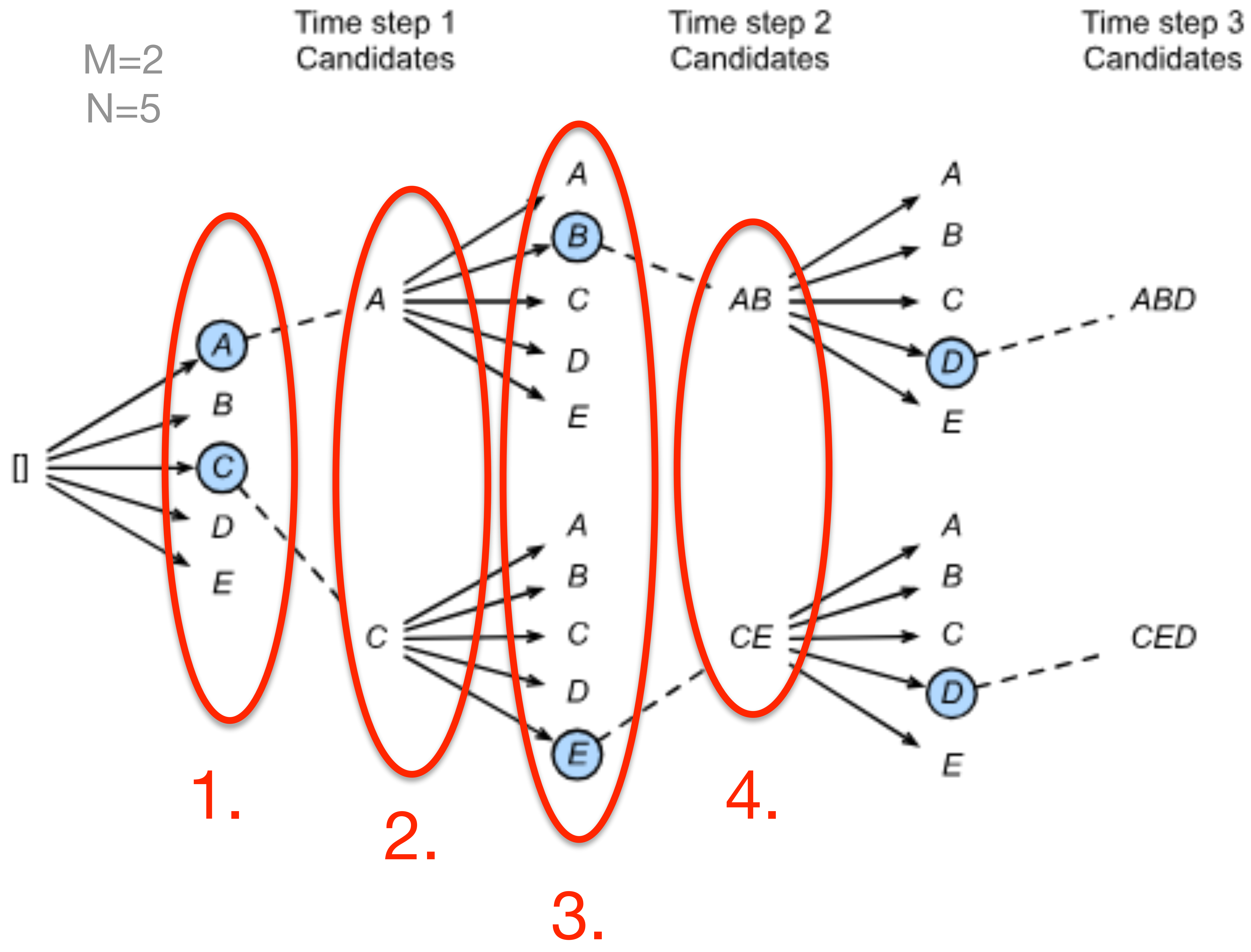
3. This gives MN candidate states.

Inference engineering: beam search



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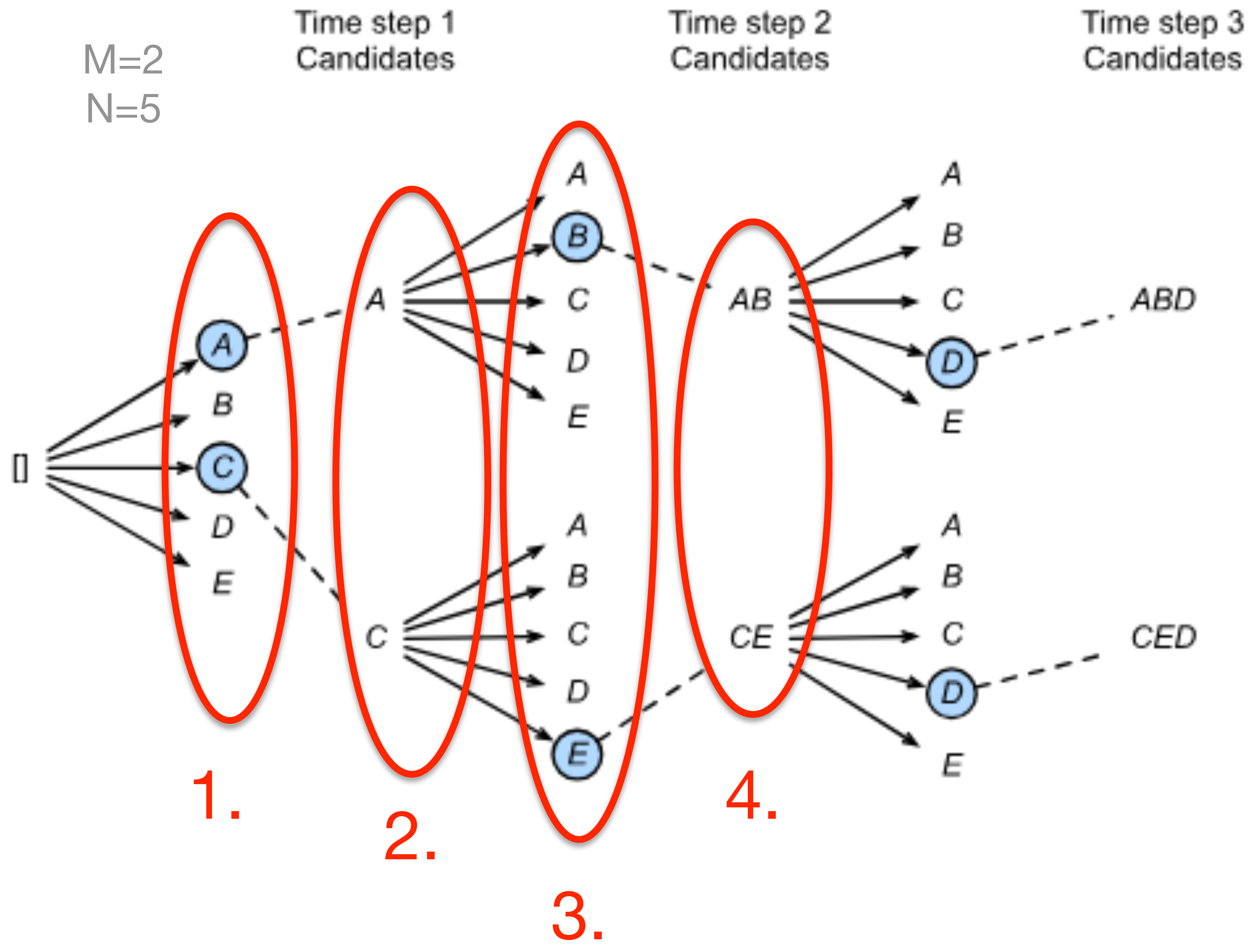

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- Beam 1: criterion = min(highest weight integral in the expression)

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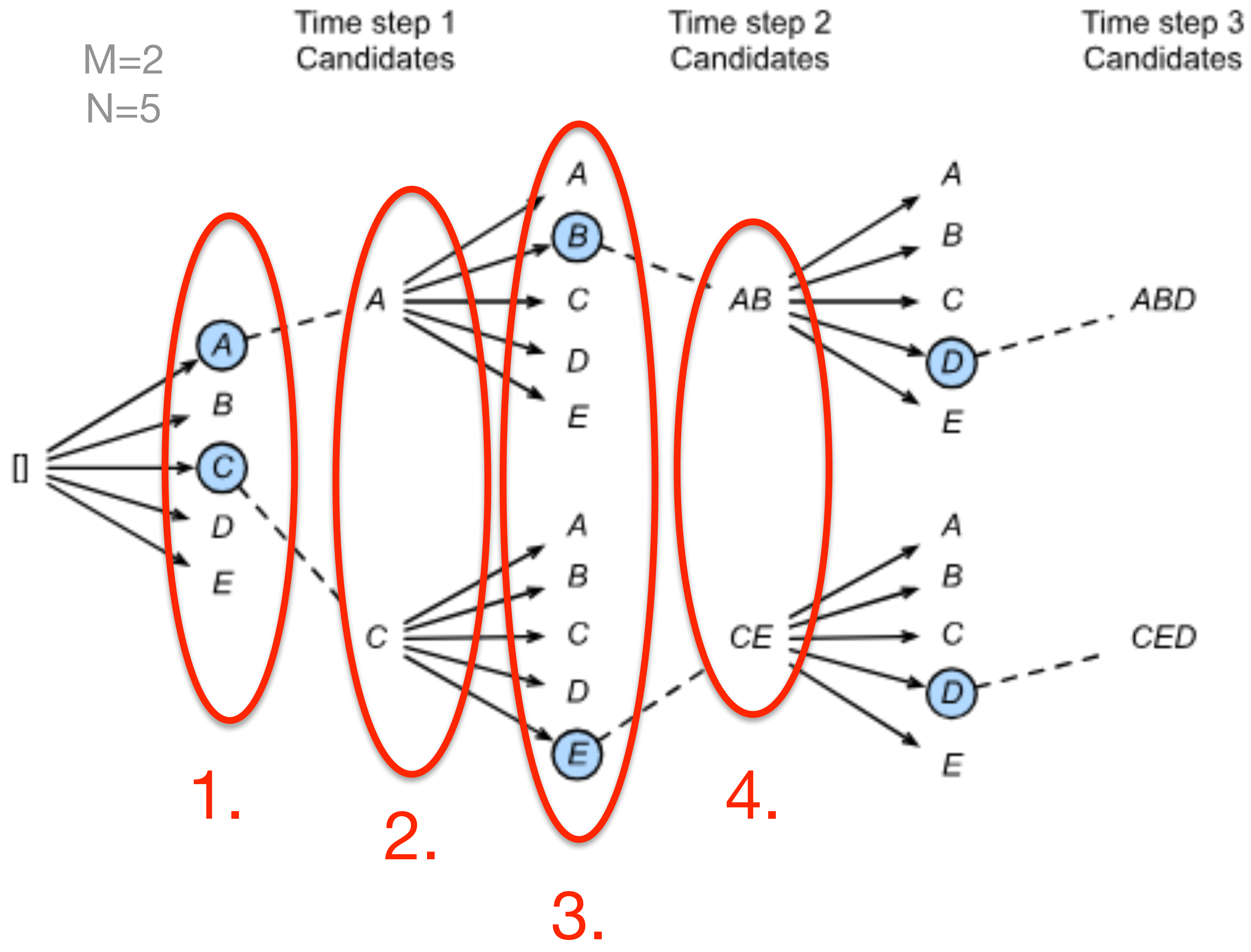

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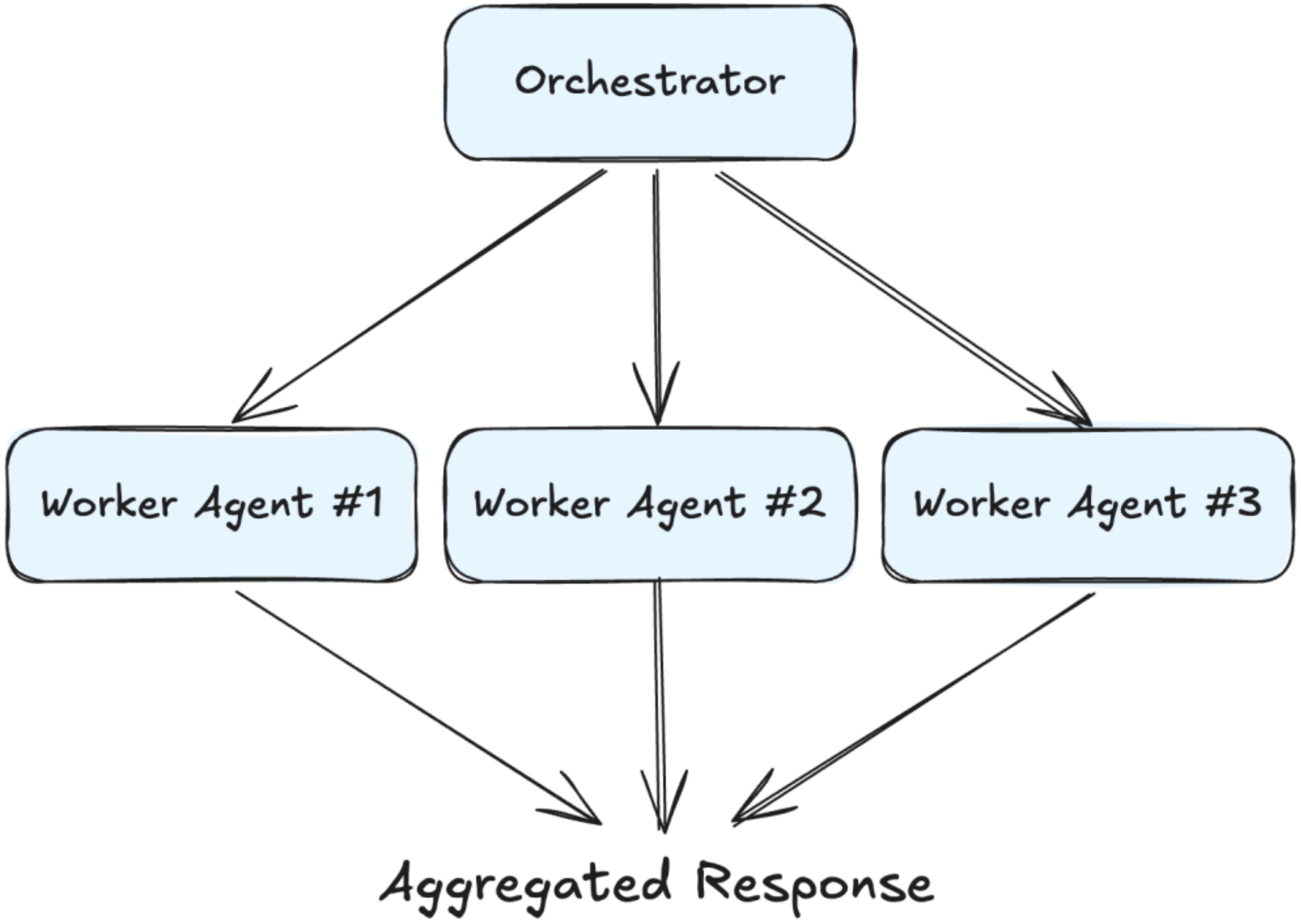
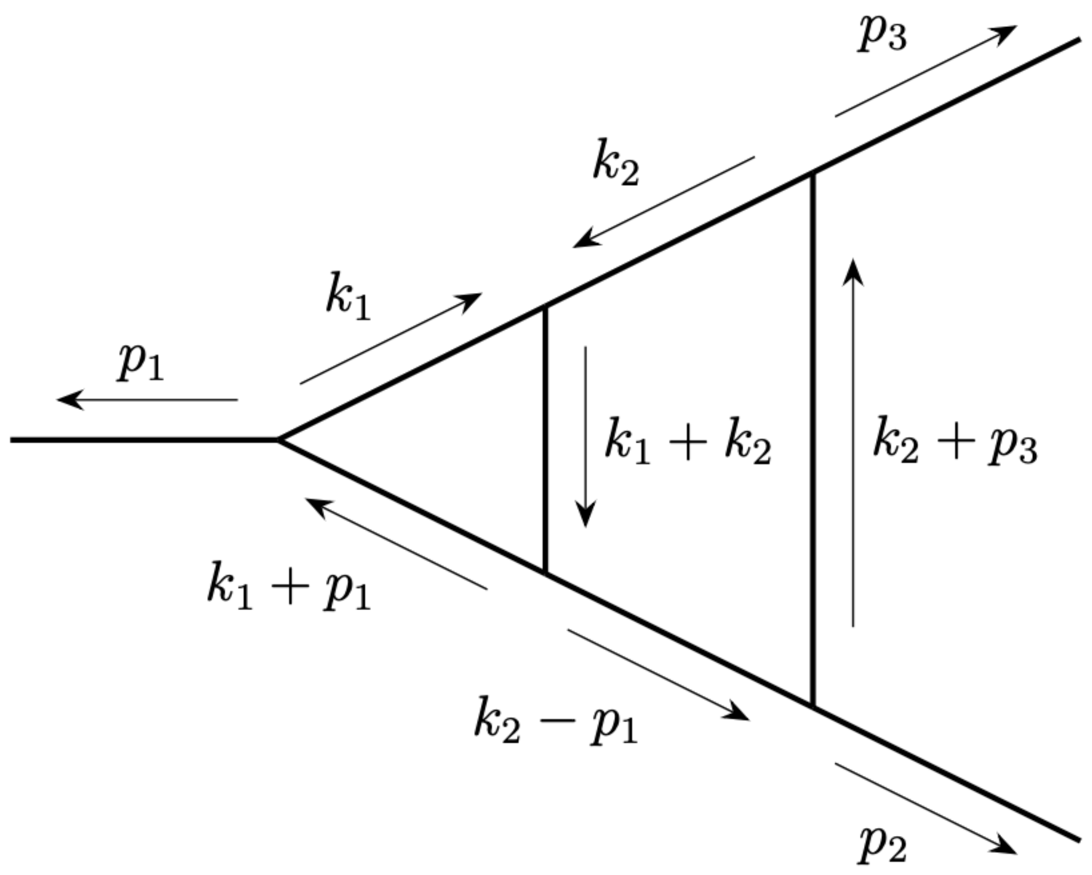
- Beam 1: criterion = min(highest weight integral in the expression)
- Beam 2: criterion = min(total summed weight of the expression)

Inference engineering: asynchronous, hierarchical, single-step reduction

- An ***orchestrator*** spawns asynchronous ***workers***
- Each worker reduces a single high weight integral by one step, modulo subsectors, in parallel
- Reduced integrals are cached, so future workers do not reinvent wheels
- Orchestrator continues until all integrals have been reduced to masters
- CPU memory used by each worker remains bounded!



Triangle-box topology



from von Hippel & Wilhelm (2025)

- 16 master integrals

$$
\begin{aligned}
&I[0,0,1,1,1,0,0], && I[0,1,1,1,0,0,0],\\
&I[0,1,1,1,1,0,0], && I[\text{-}1,1,1,1,1,0,0],\\
&I[1,0,0,1,1,1,0], && I[1,0,1,0,0,1,0],\\
&I[1,0,1,0,1,0,0], && I[1,0,1,0,1,1,0],\\
&I[1,\text{-}1,1,0,1,1,0], && I[1,0,1,1,1,0,0],\\
&I[1,\text{-}1,1,1,1,0,0], && I[1,0,1,1,1,1,0],\\
&I[1,1,0,1,0,1,0], && I[1,1,0,1,1,0,0],\\
&I[1,1,0,1,1,1,0], && I[1,1,1,1,1,0,0].
\end{aligned}
$$

$$I[a_0, a_1, a_2, a_3, a_4, a_5, a_6] = \int \frac{d^d k_1\, d^d k_2}{D_1^{a_0} D_2^{a_1} \cdots D_7^{a_6}}$$

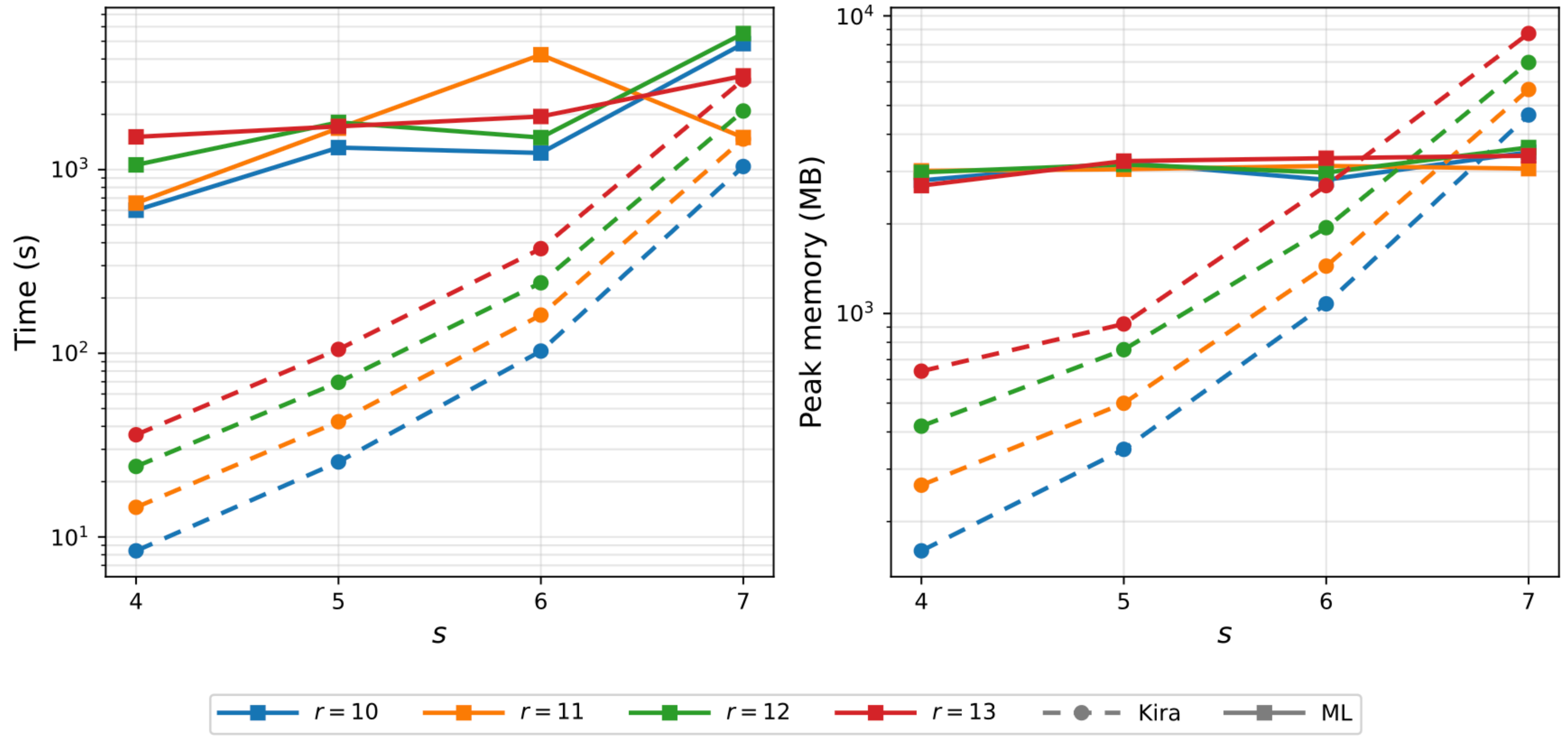
$$
\begin{aligned}
&D_1 = k_1^2, && D_2 = k_2^2,\\
&D_3 = (k_1{+}k_2)^2, && D_4 = (k_1{+}p_1)^2\\
&D_5 = (k_2{+}p_3)^2, && D_6 = (k_2{-}p_1)^2\\
&D_7 = (k_1{+}p_3)^2 \quad (\text{ISP}), &&
\end{aligned}
$$

- **Training data:** 1M training samples from randomly applying IBP identities to corner integrals

- 3 massive external momenta, 2 massless loop momenta

IBP reduction: results

r	s	Integral	r	s	Integral
10	4	$I[2,1,2,1,2,2,-4]$	10	6	$I[1,1,3,2,2,1,-6]$
11	4	$I[2,2,2,1,1,3,-4]$	11	6	$I[1,4,2,1,2,1,-6]$
12	4	$I[2,3,1,3,1,2,-4]$	12	6	$I[3,2,3,2,1,1,-6]$
13	4	$I[2,3,3,3,1,1,-4]$	13	6	$I[3,2,1,3,2,2,-6]$
10	5	$I[1,1,2,2,1,3,-5]$	10	7	$I[2,3,1,1,2,1,-7]$
11	5	$I[1,1,2,3,2,2,-5]$	11	7	$I[2,1,1,2,3,2,-7]$
12	5	$I[1,2,2,2,1,4,-5]$	12	7	$I[3,1,1,1,1,5,-7]$
13	5	$I[2,2,3,3,2,1,-5]$	13	7	$I[2,2,3,3,1,2,-7]$



- Tested on 16 triangle-box integrals with increasing weight

- SAILIR is memory stable while **Kira** memory grows rapidly with weight!

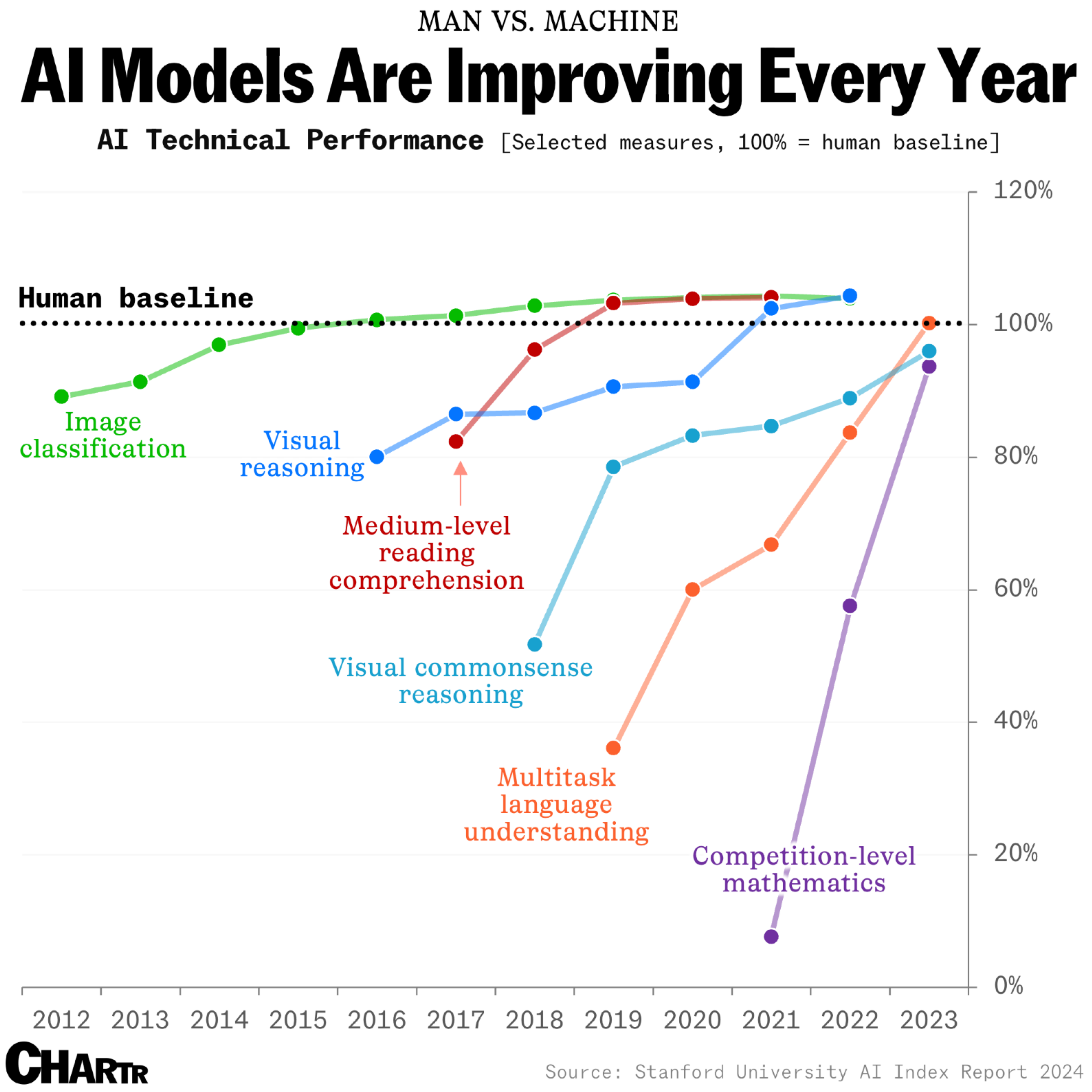
Lessons learned

- These projects were both intensely exhilarating and extremely frustrating.
- In both, Claude Code played the role of a graduate student that I interacted with entirely through text chat. Under my supervision, it wrote and ran all of the code, did all of the analysis, made all of the plots, and iterated with me on drafts of the paper.
- It was insanely fast but made tons of mistakes and kept forgetting things. Without constant close supervision and thorough validation and detailed cross checking, these projects would not have succeeded.
- Despite their flaws, I believe these agentic AI assistants will significantly lower the barrier to exploring and implementing new ideas. **Huge implications for our field!**
  - What big new questions can we now tackle that we couldn't before?
  - How do we ensure quality control? How do we handle the coming flood of papers?
  - How do we protect the future of our graduate students and postdocs? Urgently need to train them to use this amazing but flawed tool!

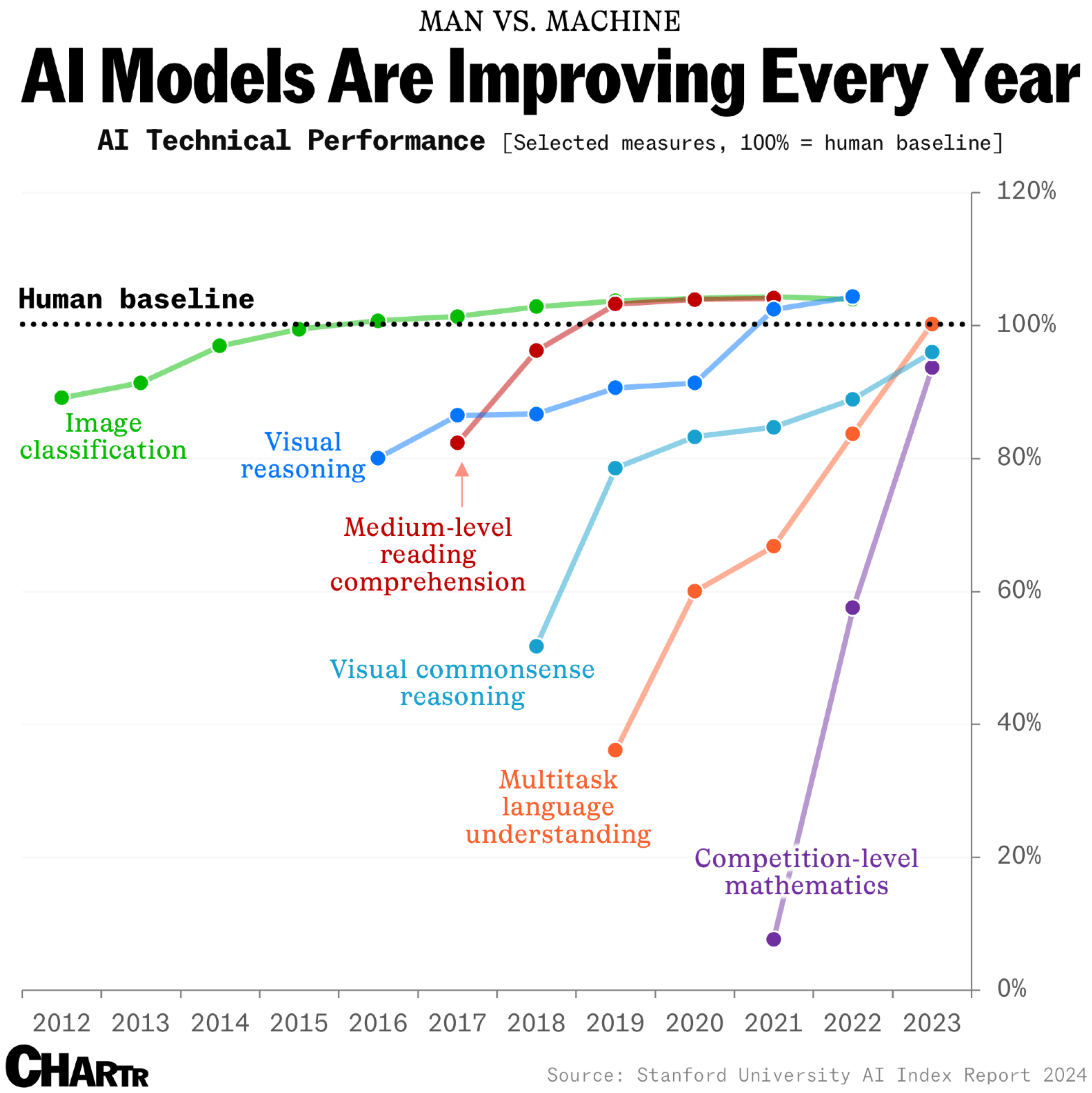
Summary

- Agentic AI is going to be a game changer for our field (and well well beyond)
- In this talk I presented two uses of agentic AI for research
  - As a hands-on research assistant -> two papers on “Learning to Unscramble”, applications to scattering amplitudes and Feynman loop integral reduction
  - As a fully automated system for reproducing LHC analyses (an important and common task in pheno research)

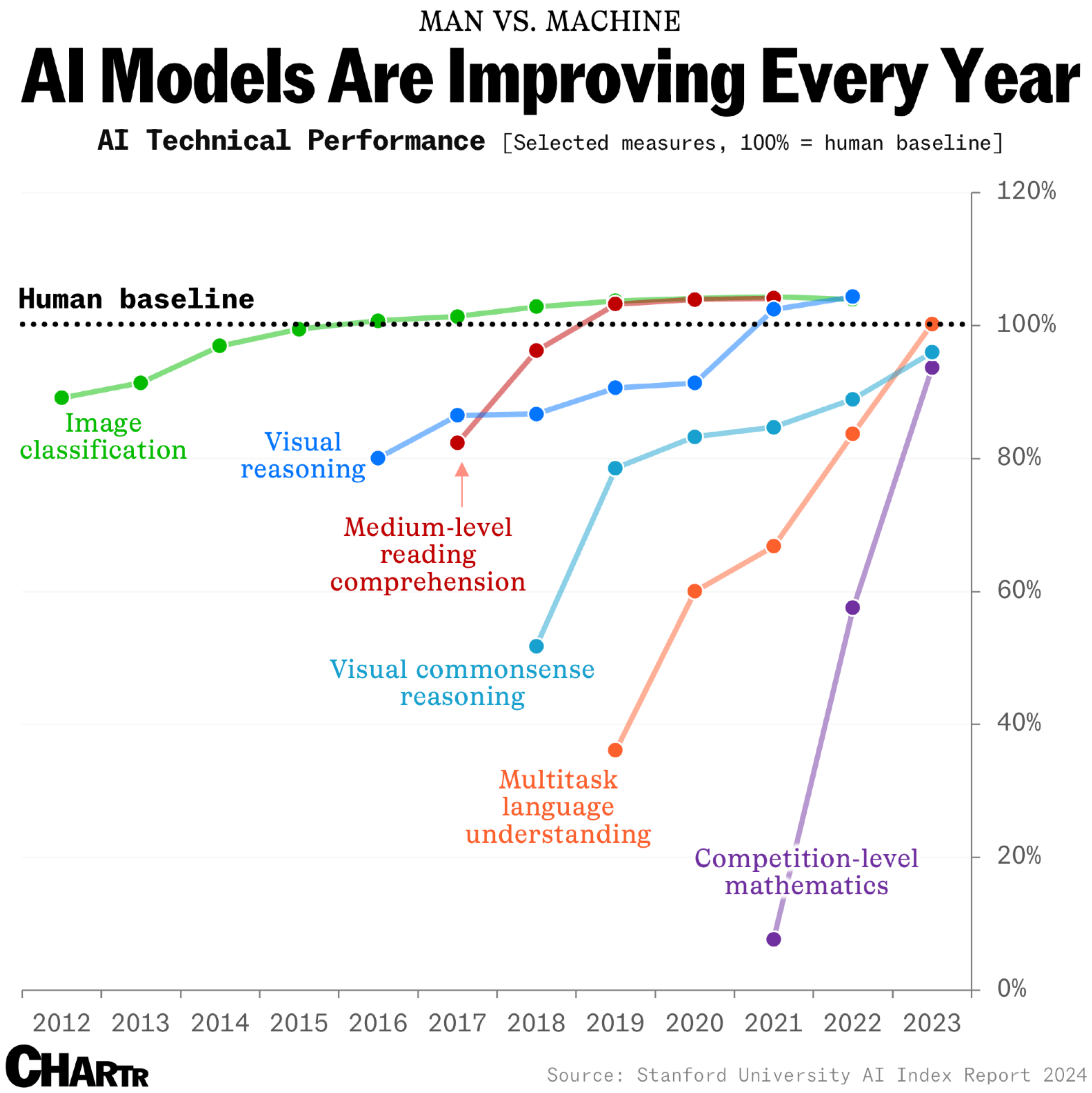
Where are we headed?



Where are we headed?



Where are we headed?

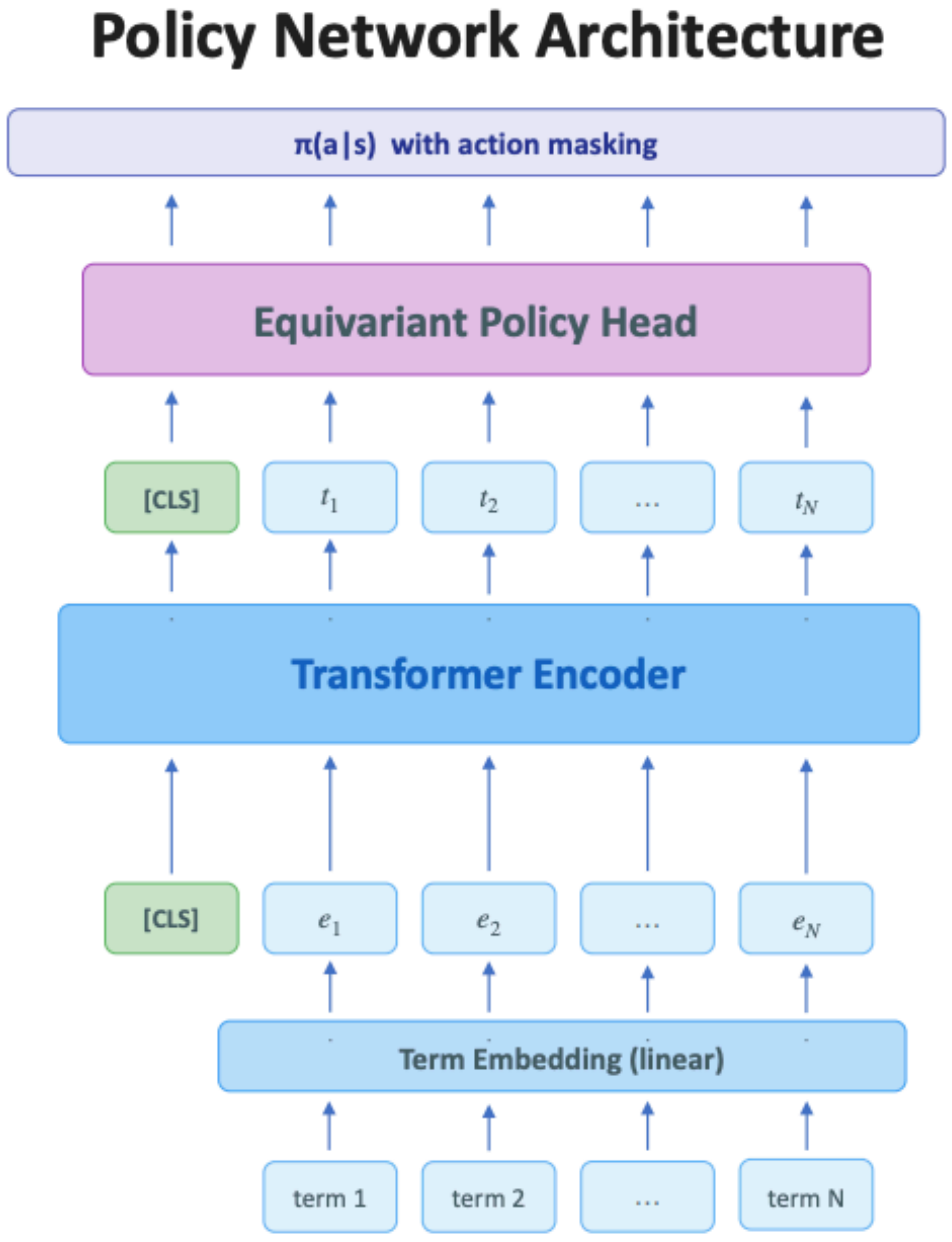


Or will AI models plateau into a superpowered research tool?

Thanks!

Scattering amplitudes: setup

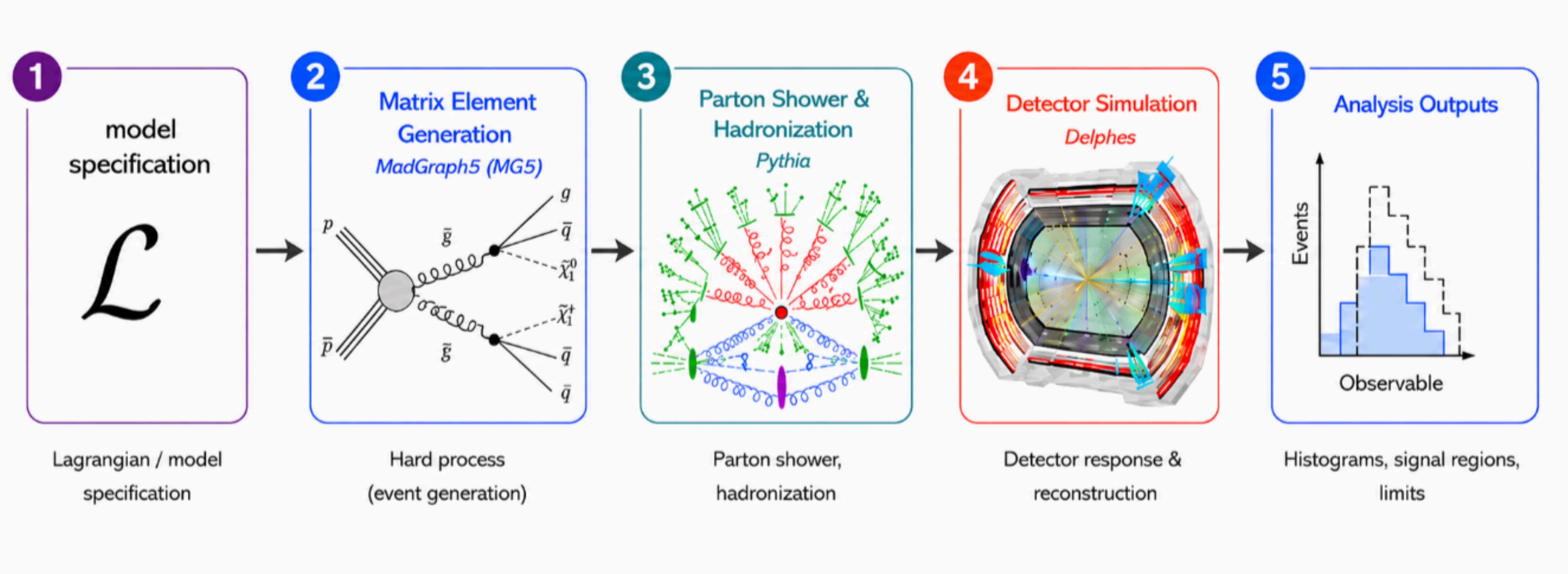
- **Permutation-equivariant action classifier:** interchanging order of terms should change action classifier output correspondingly
- Action space [~1.4k for 4 pts, ~4k for 5 pts and ~30k for 6 pts] — choice of:
  - term (up to 10 for 4-5pts, 30 for 6 pts)
  - bracket type
  - momentum
- Term encoding — for each factor (up to 8):
  - coefficient
  - bracket type
  - momenta
  - power



Bonus material: ColliderBench

[Faroughy, Palacios Schweitzer, Pang, Mishra Sharma, DS 2605.13950]

- A new benchmark for evaluating LLM agents on automated, long-horizon, real-world scientific tasks
- Setting: reproducing published LHC analyses (new physics searches) using public simulation tools — “recasting”



Challenges

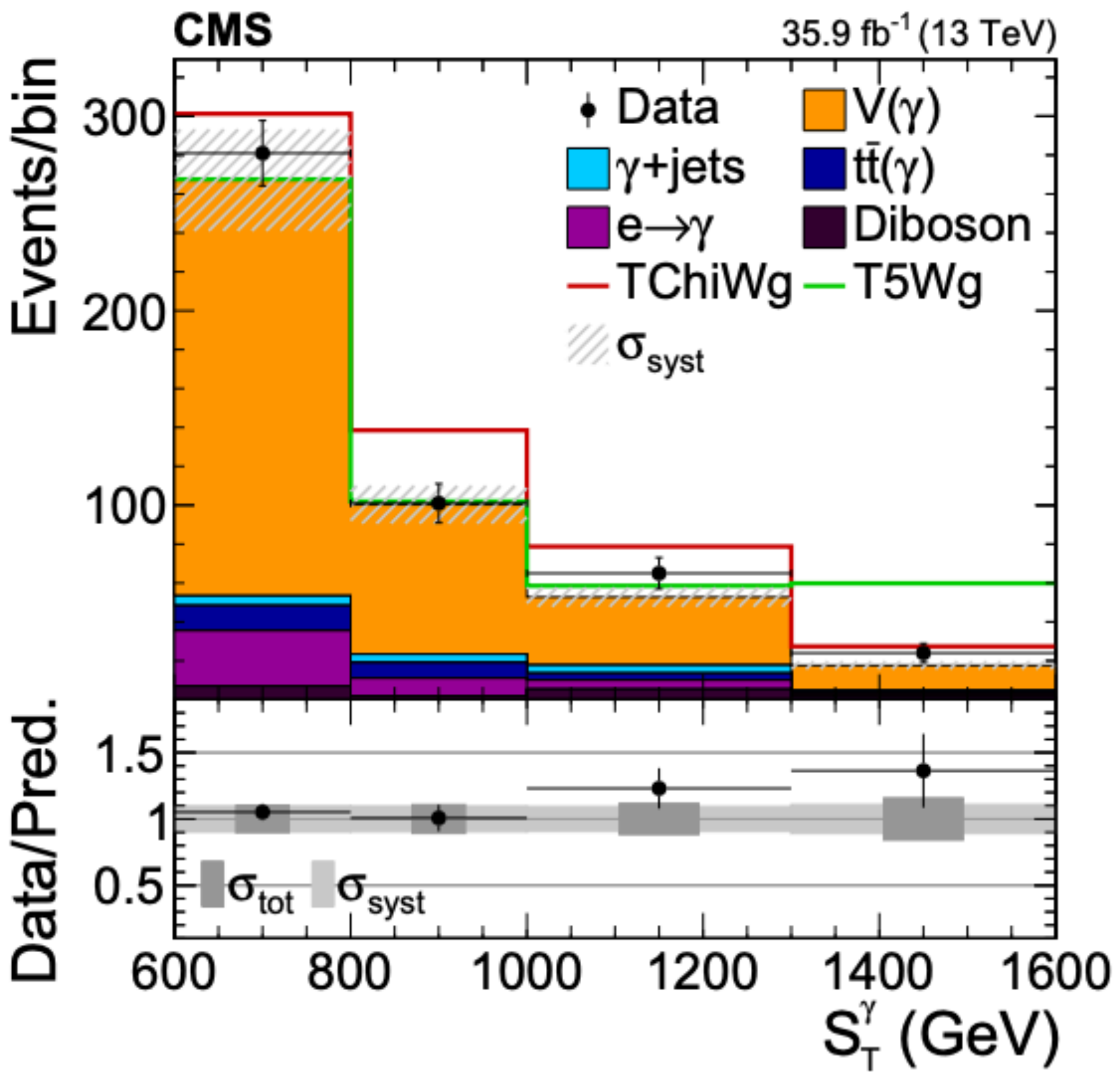
- Unique challenges:
  - experimental papers from CMS and ATLAS often missing crucial details, inaccuracies, errors.
  - Gap between public simulation tools and proprietary CMS/ATLAS tools, correction factors, etc
  - Agent cannot get a perfect reproduction. Needs combination of physical intuition, domain knowledge, guesswork

ColliderBench: inputs

- Paper (PDF) from CMS/ATLAS

Table 1: Summary of the event selection criteria required for the control, validation, and signal regions.

Region	Selection
Preselection	$p_{\mathrm{T}}^{\mathrm{miss}}$ filters At least one reconstructed vertex At least one photon with $p_{\mathrm{T}} > 180\,\mathrm{GeV}$ $\Delta R(\gamma, \mathrm{jet}) > 0.5$ $\Delta\phi(\vec{p}_{\mathrm{T}}^{\mathrm{miss}}, \mathrm{jet}) > 0.3\,\mathrm{rad}$, if $p_{\mathrm{T}}(\mathrm{jet}) > 100\,\mathrm{GeV}$
Control region	Preselection $p_{\mathrm{T}}^{\mathrm{miss}} > 100\,\mathrm{GeV}$ $M_{\mathrm{T}}(\gamma, \vec{p}_{\mathrm{T}}^{\mathrm{miss}}) > 100\,\mathrm{GeV}$ $p_{\mathrm{T}}^{\mathrm{miss}} < 300\,\mathrm{GeV}$ or $M_{\mathrm{T}}(\gamma, \vec{p}_{\mathrm{T}}^{\mathrm{miss}}) < 300\,\mathrm{GeV}$
Validation region	Preselection $p_{\mathrm{T}}^{\mathrm{miss}} > 300\,\mathrm{GeV}$ $M_{\mathrm{T}}(\gamma, \vec{p}_{\mathrm{T}}^{\mathrm{miss}}) > 300\,\mathrm{GeV}$ $S_{\mathrm{T}}^{\gamma} < 600\,\mathrm{GeV}$
Signal region	Preselection $p_{\mathrm{T}}^{\mathrm{miss}} > 300\,\mathrm{GeV}$ $M_{\mathrm{T}}(\gamma, \vec{p}_{\mathrm{T}}^{\mathrm{miss}}) > 300\,\mathrm{GeV}$ $S_{\mathrm{T}}^{\gamma} > 600\,\mathrm{GeV}$



Search for gauge-mediated supersymmetry in events with at least one photon and missing transverse momentum in pp collisions at $\sqrt{s} = 13\,\mathrm{TeV}$

The CMS Collaboration*

Abstract

A search for gauge-mediated supersymmetry (SUSY) in final states with photons and large missing transverse momentum is presented. The data sample of pp collisions at $\sqrt{s} = 13\,\mathrm{TeV}$ was collected with the CMS detector at the CERN LHC and corresponds to an integrated luminosity of $35.9\,\mathrm{fb}^{-1}$. Data are compared with models in which the lightest neutralino has bino- or wino-like components, resulting in decays to photons and gravitinos, where the gravitinos escape detection. The event selection is optimized for both electroweak (EWK) and strong production SUSY scenarios. The observed data are consistent with standard model predictions, and limits are set in the context of a general gauge mediation model in which gaugino masses up to 980 GeV are excluded at 95% confidence level. Gaugino masses below 780 and 950 GeV are excluded in two simplified models with EWK production of mass-degenerate charginos and neutralinos. Stringent limits are set on simplified models based on gluino and squark pair production, excluding gluino (squark) masses up to 2100 (1750) GeV depending on the assumptions made for the decay modes and intermediate particle masses. This analysis sets the highest mass limits to date in the studied EWK models, and in the considered strong production models when the mass difference between the gauginos and the squarks or gluinos is small.

ColliderBench: inputs

- Task specification prompt
  - new physics signal to simulate
  - histogram from paper to reproduce
  - other output requirements

TASK.md

Paper: CMS-SUS-16-046
Centre-of-mass energy: 13 TeV
Luminosity: 35.9 fb^{-1}
Task type: simulation (shape-only)
Signal benchmark: `TChiWg_700`
Observable: S_T^γ

Task

Implement the search analysis described in **CMS-SUS-16-046** and use it to predict the normalized event distribution (shape) of S_T^γ for the signal benchmark point `TChiWg_700`, in the analysis's signal region. The agent should:

1. Generate `TChiWg_700` events using a matrix-element generator, parton shower, and detector simulation chain of its choice.
2. Read the paper to determine the object identification, event-selection requirements, and signal-region cuts that define the analysis, then apply them to the generated events.
3. Histogram the surviving events in S_T^γ using the bin edges already present in the `results/*.yaml` template. The bin edges must not be modified.

Definitions

- S_T^γ is the scalar sum of p_T^{miss} and the transverse momenta of all photons in the event.
- `TChiWg_700` denotes electroweak associated production of mass-degenerate winos at $m(\widetilde{W}) =$ 700 GeV, decaying to a massless gravitino LSP and Standard Model gauge bosons, with at least one photon in the final state through the `TChiWg` simplified-model topology.

Output requirements

Artifact	Purpose
`results/*.yaml`	Fill null bin values with predicted relative signal bin contents.
`analysis/*.py`	Event-selection code, runnable on the generated sample.
`data/*.root`, `sims/*.dat`	Selected-event files and generator/detector cards.
`report.md`	Methodological choices and deviations from the paper.

Important

The goal is to predict the signal shape from the agent's own simulation and analysis pipeline. The agent must not extract or digitize the target bin values from the paper's figures, tables, or HEPData record.

ColliderBench: inputs

- HEP toolbox
  - md files that teach agents how to use HEP software tools

````markdown
# Simulation stack — MadGraph5 / Pythia8 / Delphes

**Purpose.** Generate signal events end-to-end (parton-level → parton
shower → detector simulation) when no matching MC is available in CMS
Open Data. The CLIs are simple enough that there's no wrapper; you call
them directly. `bin/simulate info` lists installed models and cards;
`bin/simulate --doc` shows this page.

**When to use.** For BSM signals the paper defines but nobody has
produced for Open Data (SUSY benchmark points, EFT signals, etc.). For
SM backgrounds you usually want `cms-opendata` instead — save compute.

---

## Quick discovery

```bash
bin/simulate info        # installed UFO models + Delphes cards + tool paths
bin/simulate --doc       # this page
```

The relevant env vars (set inside the bench image; fall back to the
in-repo paths otherwise):
````

````markdown
# `feynrules` — browse and download UFO models from the FeynRules database

**Purpose.** If the bundled MadGraph UFO models (`sm`, `MSSM_SLHA2`,
`SMEFTsim`) don't cover your paper's BSM scenario, fetch an additional
model from the FeynRules wiki.

**When to use.** Only when `bin/simulate info` doesn't already list a
suitable UFO. For standard SUSY / SMEFT / top-EFT the bundled models are
usually enough.

## Invocation

```bash
bin/feynrules categories                             # 7 top-level categories
bin/feynrules list --category SusyModels             # browse one category
bin/feynrules list --search "vector-like quark"      # substring search over slug/title/description
bin/feynrules info <model-slug>                      # show all attachments for a model
bin/feynrules fetch <model-slug> [--file <name>] [--all] [--dest <dir>] [--extract]
bin/feynrules refresh-catalog                        # re-scrape the wiki (catalog is cached)
```
````

ColliderBench: metrics

$$d(\hat{y}, y^{\star}) = \sqrt{\frac{\sum_{k=1}^{K} \left(\hat{y}_k - y_k^{\star}\right)^2}{\sum_{k=1}^{K} {y_k^{\star}}^2}}.$$

L2 histogram distance

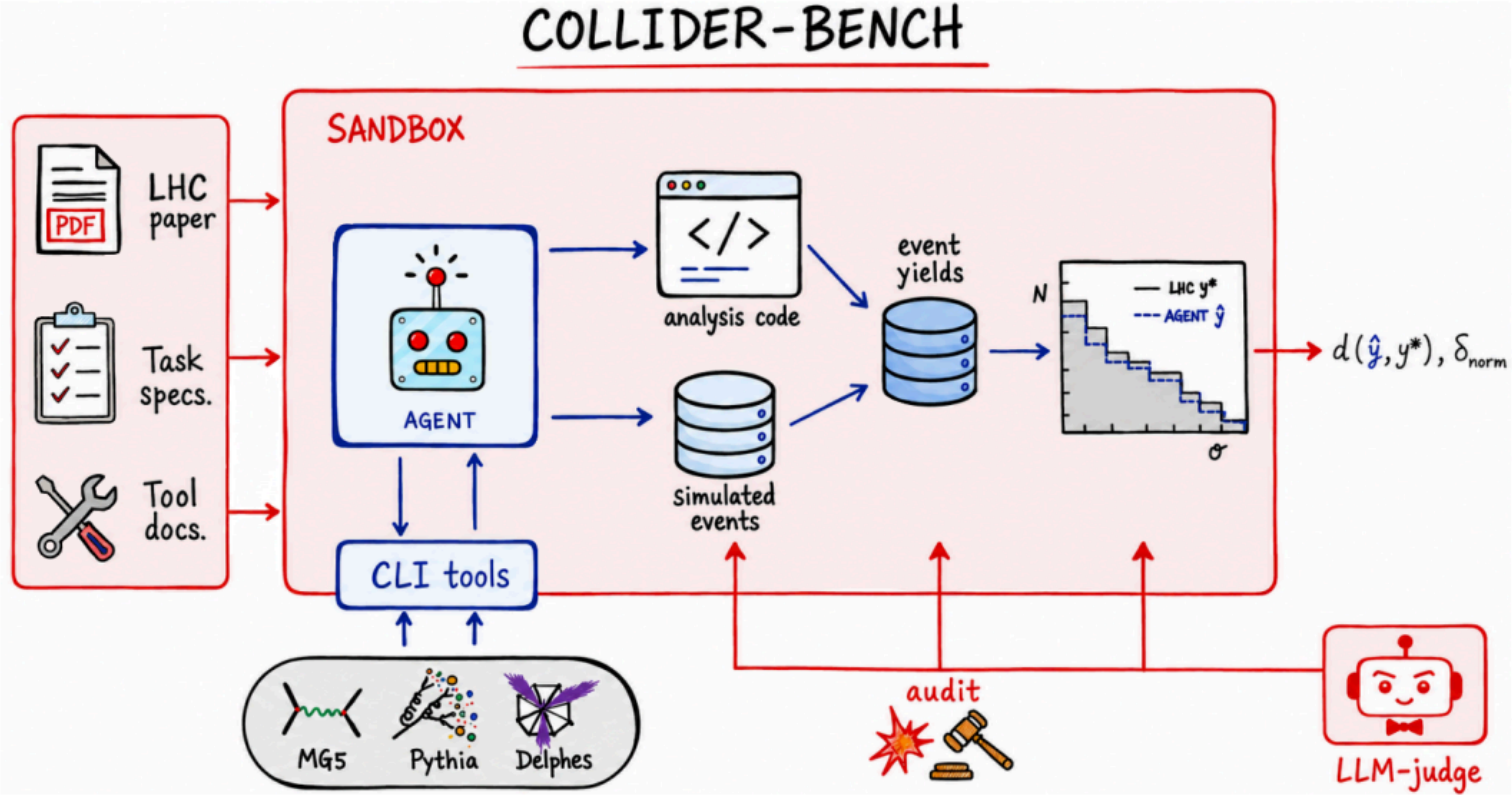
$$\delta_{\mathrm{norm}} = \frac{|\hat{Y} - Y^{\star}|}{Y^{\star}}.$$

normalization error

$$\mathrm{Acc}_{\tau} = \mathbb{I}[d_{\mathrm{task}} < \tau]\,,$$

pass/fail metric

ColliderBench: overview



LLM judge to catch cheating, hallucinations

ColliderBench V1

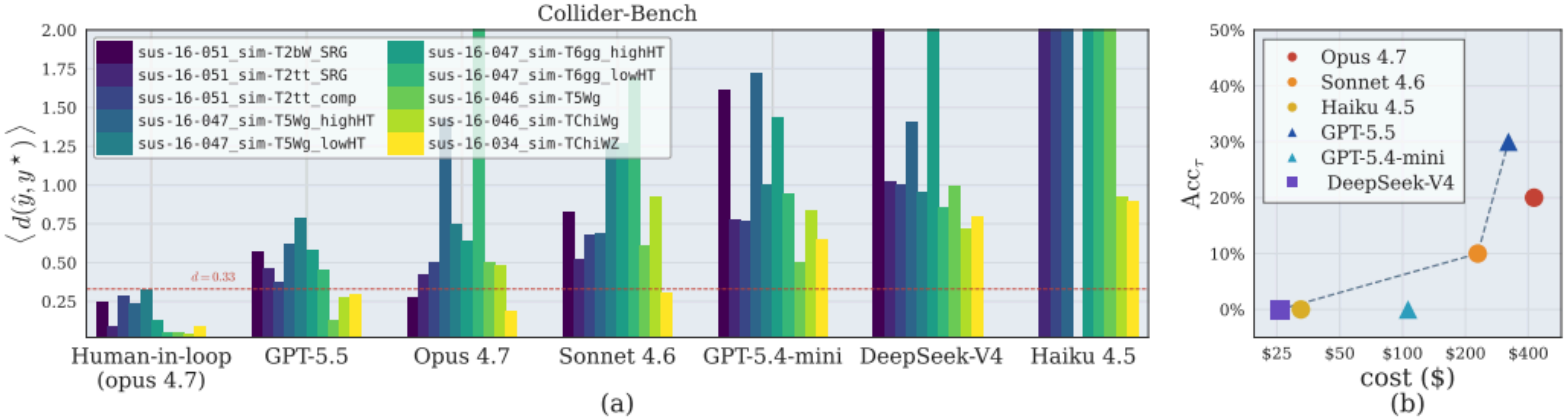
- 10 tasks over 4 CMS supersymmetry searches from ~2016 (13 TeV, 36/fb)

Table 1: Source analyses and simulation tasks in COLLIDER-BENCH. Each task fixes a paper, signal benchmark, target observable or signal region, and output template. Difficulty is graded from the relative-L^2 residual of our physicist-in-the-loop reproduction of each task: ★ (easy), ★★ (medium), ★★★ (hard).

Task	Analysis target	Signal s	obs. $\mathcal{O}$	LHC search	Reference	Diff.
`sus-16-034_sim-TChiWZ`	leptons + jets	`TChiWZ`	E_T^{miss}	CMS-SUS-16-034	Sirunyan et al. [2018b]	★
`sus-16-046_sim-T5Wg`	photons	`T5Wg`	S_T^{γ}	CMS-SUS-16-046	Sirunyan et al. [2018a]	★
`sus-16-046_sim-TChiWg`	photons	`TChiWg`	S_T^{γ}	CMS-SUS-16-046	Sirunyan et al. [2018a]	★
`sus-16-047_sim-T5Wg_highHT`	photons	`T5Wg`, high-H_T	p_T^{miss}	CMS-SUS-16-047	Sirunyan et al. [2017b]	★★
`sus-16-047_sim-T5Wg_lowHT`	photons	`T5Wg`, low-H_T	p_T^{miss}	CMS-SUS-16-047	Sirunyan et al. [2017b]	★★★
`sus-16-047_sim-T6gg_highHT`	photons	`T6gg`, high-H_T	p_T^{miss}	CMS-SUS-16-047	Sirunyan et al. [2017b]	★★
`sus-16-047_sim-T6gg_lowHT`	photons	`T6gg`, low-H_T	p_T^{miss}	CMS-SUS-16-047	Sirunyan et al. [2017b]	★
`sus-16-051_sim-T2tt`	single lepton	`T2tt`	E_T^{miss}	CMS-SUS-16-051	Sirunyan et al. [2017a]	★
`sus-16-051_sim-T2tt_comp`	single lepton	`T2tt`, compressed	E_T^{miss}	CMS-SUS-16-051	Sirunyan et al. [2017a]	★★★
`sus-16-051_sim-T2bW`	single lepton	`T2bW`	E_T^{miss}	CMS-SUS-16-051	Sirunyan et al. [2017a]	★★

- Hundreds of more tasks and searches available, will be added for V2!

ColliderBench: results



- Clear capability ladder
  (Opus>Sonnet>Haiku; GPT5.5>GPT-5.4-mini)
- Clear Pareto front in pass/fail vs cost
- No LLM agent beats human-in-the-loop