

# Machine Learning the S-Matrix

String Data 2024

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# Outline

## 1. S-matrix bootstrap

Based on “Reconstructing S-matrix Phases with Machine Learning”

- arXiv:2308.09451
- with Aurelian Dersy (Harvard) and Sasha Zhiboedov (CERN)

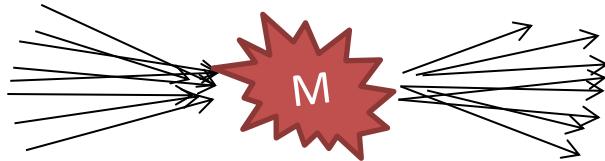
## 2. Simplifying spinor-helicity amplitudes

Based on “Learning the simplicity of scattering amplitudes”

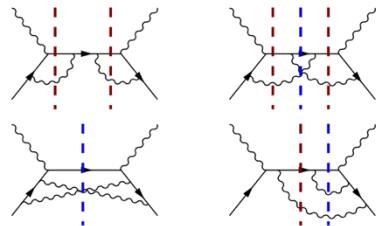
- arXiv:2408.04720
- with Aurelian Dersy (Harvard) and Cliff Cheung (Caltech)

# The S-Matrix

The S-matrix is the fundamental object of Quantum Field Theory



- A lot is known about it from perturbation theory (Feynman diagrams)



computation



- spinor-helicity amplitudes
- twistor space
- multiple-polylogarithms
- amplituhedron

- Some things are known/conjectured about it non-perturbatively
  - e.g. it should be unitary, analytic and satisfy crossing relations
  - it cannot grow with energy faster than  $\log^2 E$  (Froissart bound)

Can ML help understand the S-matrix?

# 1. Can ML help with the non-perturbative S-matrix?

[ Dersy, MDS, Zhiboedov, 2308.09451 ]

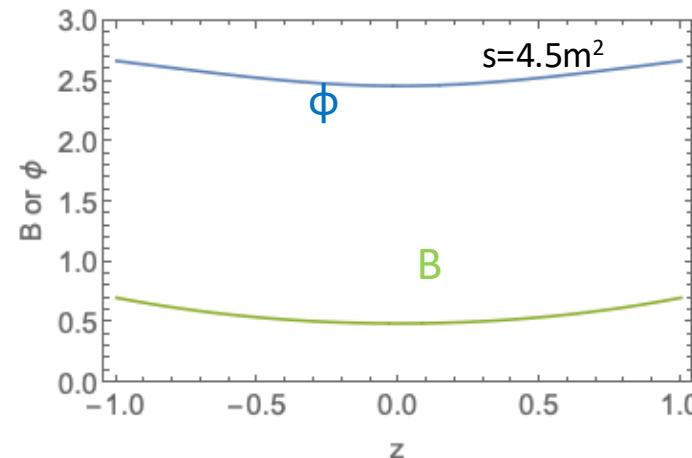
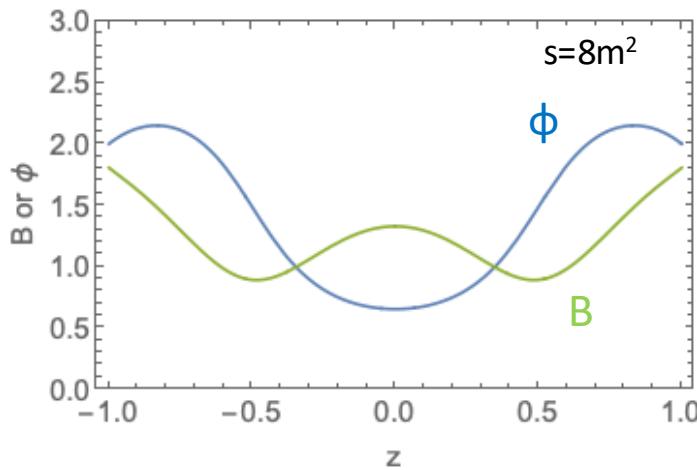
What does this mean?

- Use analyticity, unitarity, crossing symmetry to determine S

Example questions:

For a given cross section  $\sigma = |A|^2$

- Does there always exist a phase  $\phi$  so that  $A = B e^{i\phi}$ ?
- e.g. Penedones et al 1708.06756, Fitzpatrick et al 2207.12448 found  $(B, \phi)$  pairs



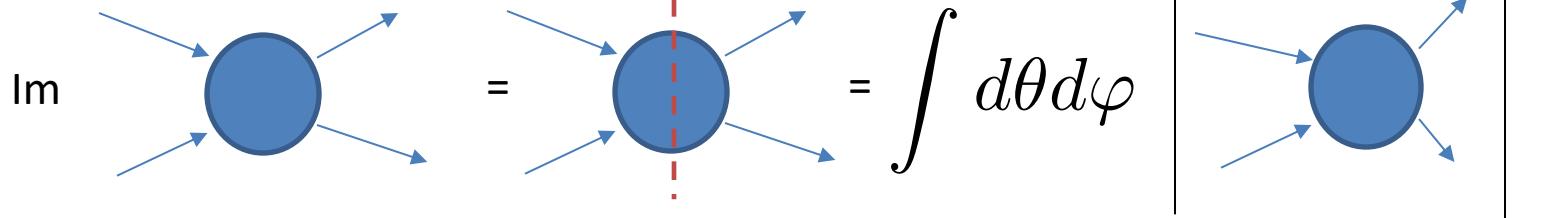
Two questions ML can help with

1. Can we determine  $\phi$  from  $B$ ?
2. Can there be many phases  $\phi_1, \phi_2, \dots$  for the same  $B$ ?

# Elastic scattering

Focus on the elastic scattering region

- $4 \text{ m}^2 < s < 9 \text{ m}^2$
- Only 2-particle cuts



- Only states with fixed total energy are relevant
- States characterized by scattering angle  $z = \cos\theta$

We write  $\mathcal{M}(z) = B(z) e^{i\phi(z)}$

Unitarity constraint  $\text{Im}\mathcal{M}(z) = \int d\Pi |B|^2$

$$\Rightarrow B(z_{12}) \sin \phi(z_{12}) = \frac{1}{4\pi} \int d\Omega_3 B(z_{13}) B(z_{23}) \cos(\phi(z_{13}) - \phi(z_{23}))$$

$$\Rightarrow \boxed{\sin \phi(z) = \frac{\int_{-1}^1 dz_1 \int_0^{2\pi} d\phi_1 B(z_1) B(z_2) e^{i\phi(z_1) - i\phi(z_2)}}{4\pi B(z)}}$$

$$z_2 = z z_1 + \sqrt{1 - z^2} \sqrt{1 - z_1^2} \cos \phi_1$$

Does  $\phi(z)$  exist satisfying this equation for a given  $B(z)$ ?

# Elastic scattering

$$\sin \phi(z) = \frac{\int_{-1}^1 dz_1 \int_0^{2\pi} d\phi_1 B(z_1) B(z_2) e^{i\phi(z_1) - i\phi(z_2)}}{4\pi B(z)} \xrightarrow{\text{set phase to zero}} \leq \max_z \frac{\int_{-1}^1 dz_1 \int_0^{2\pi} d\phi_1 B(z_1) B(z_2)}{4\pi B(z)} \equiv \sin \mu$$

Martin (1969) proved that

- If  $\sin \mu < 1$  for a given  $B(z)$  then there always exists a phase  $\phi(z)$
- easy to find examples of  $B(z)$  with  $\sin \mu > 1$  for which no phase exists

e.g. if  $B(z) = B$  and  $\phi(z) = \phi$  are constants then

$$\sin \varphi = \frac{\int_{-1}^1 dz_1 \int_0^{2\pi} d\phi_1 B^2 e^{i(\varphi - \varphi)}}{4\pi B} = B = \sin \mu \quad \rightarrow \quad \text{If } B > 1 \text{ then no phase exists}$$

- If  $\sin \mu < 0.79$  then the phase is unique
  - Later, Gangal and Kupsch (1984) extended uniqueness proof to  $\sin \mu < 0.89$
  - Crichton (1966) found an example with multiple phases for same the  $B$  with  $\sin \mu = 3.2$
  - Atkinson (1977) found an example with multiple phases with  $\sin \mu = 2.15$

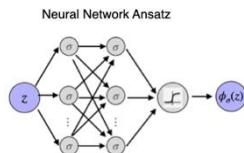
Open  
questions

- Can **0.89** be raised?
- Can **2.15** be lowered?
- How can we construct  $\phi$  when it exists?

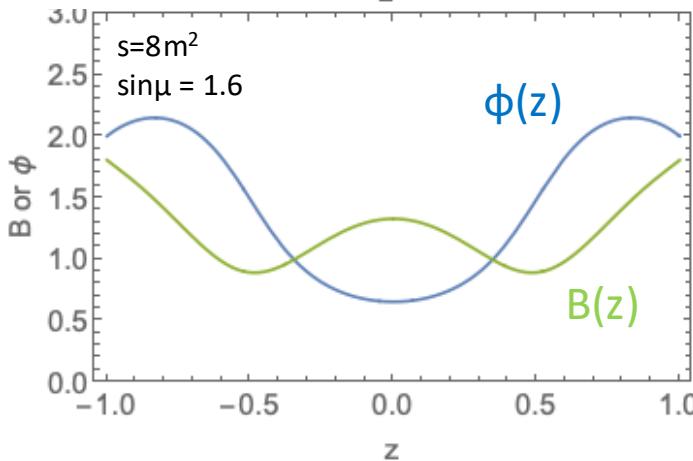
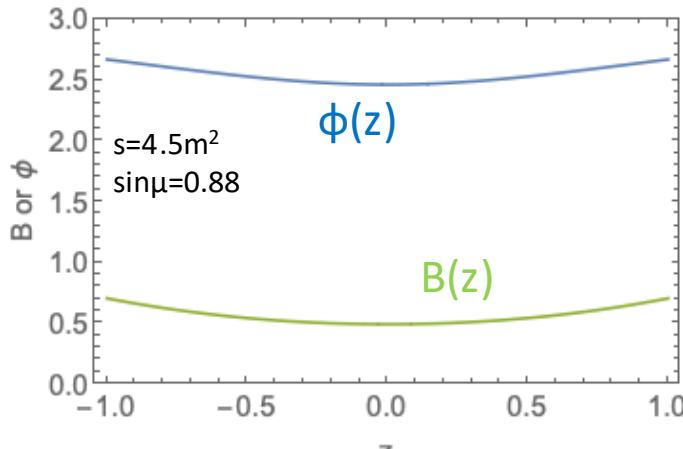
Can we find  $\phi(z)$  given  $B(z)$  with ML? ... Yes!

[ Dersy, MDS, Zhiboedov, 2308.09451 ]

- Parametrize  $\phi(z)$  as a neural network
- Loss function is unitarity condition



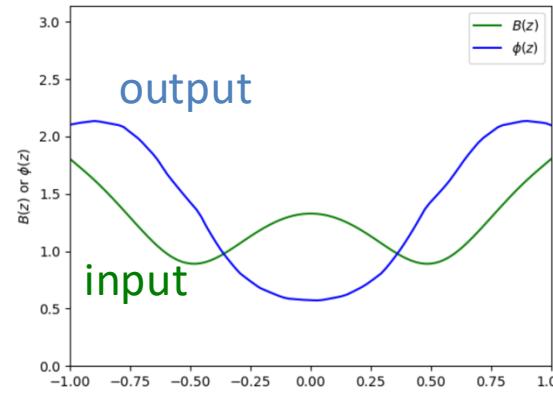
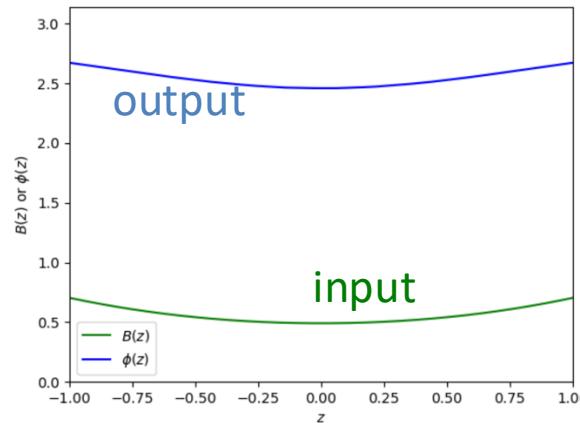
## some known examples



- Loss function is unitarity condition

$$\mathcal{L} = \mathbb{E} \left| B(z) \sin \phi(z) - \frac{1}{4\pi} \int_{-1}^1 dz_1 \int_0^{2\pi} d\phi_1 B(z_1) B(z_2) \cos(\phi(z_1) - \phi(z_2)) \right|^2$$

## ML solutions



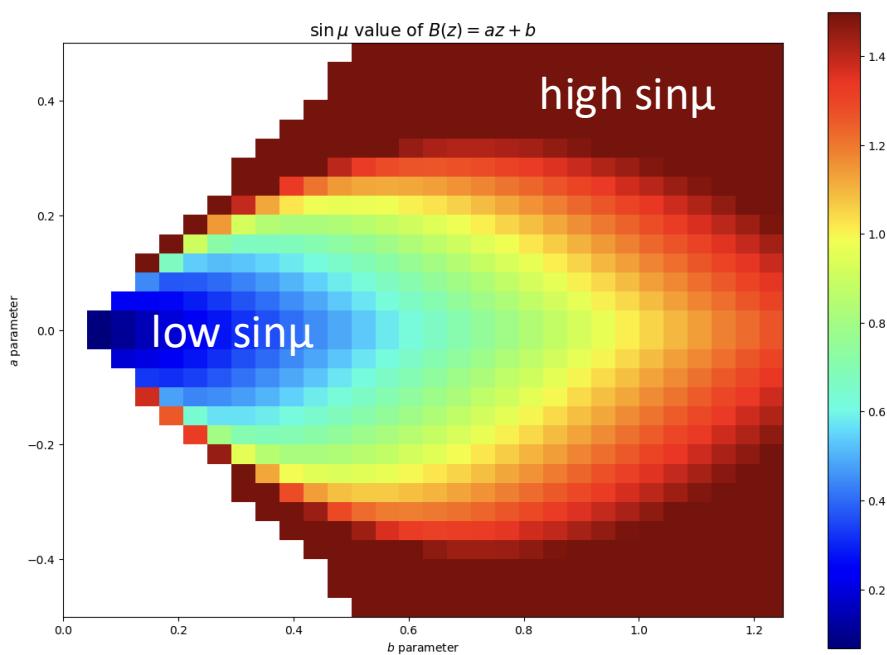
excellent  
agreement  
with known  
results

# Loss as a proxy for $\sin \mu$

Consider functions  $B(z) = a z + b$

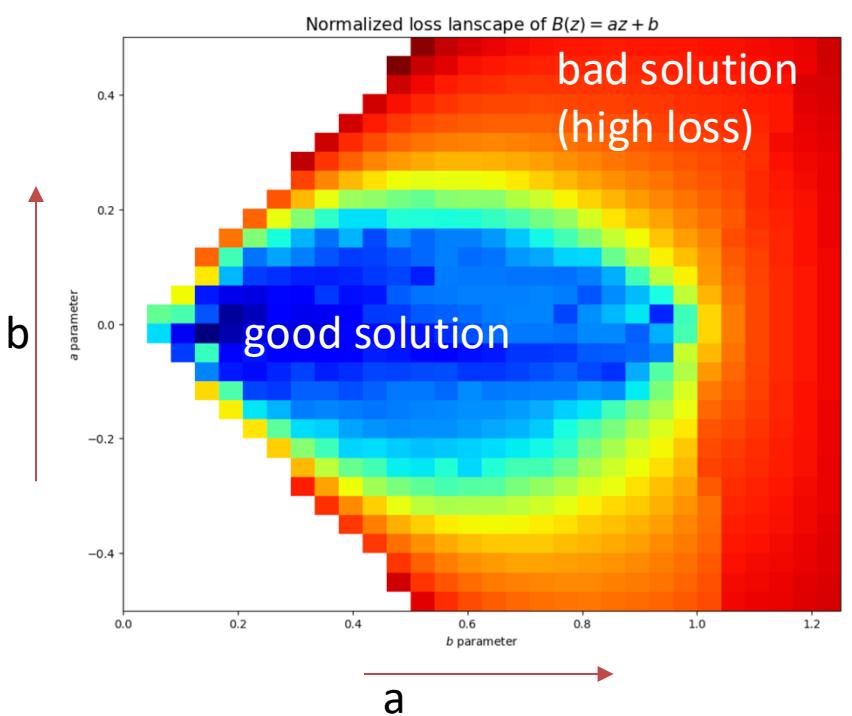
- Use ML to find  $\phi(z)$

Contours of  $\sin \mu$



$$\sin \mu = \max_z \frac{\int_{-1}^1 dz_1 \int_0^{2\pi} d\phi_1 B(z_1) B(z_2)}{4\pi B(z)}$$

Loss landscape from ML search for  $\phi$



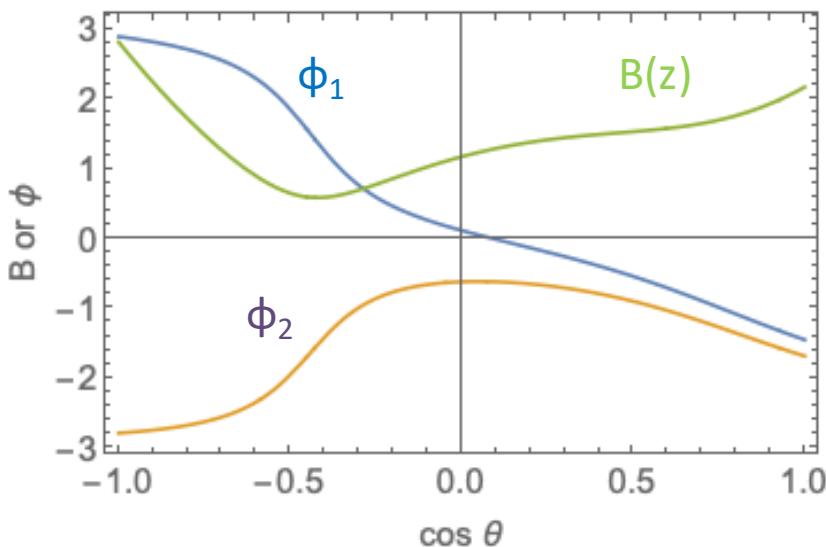
- Totally different things have similar contours
- Don't need an exact solution to learn something:
  - suggests high  $\sin \mu$  solutions will be hard to find

# Is the phase always unique? No!

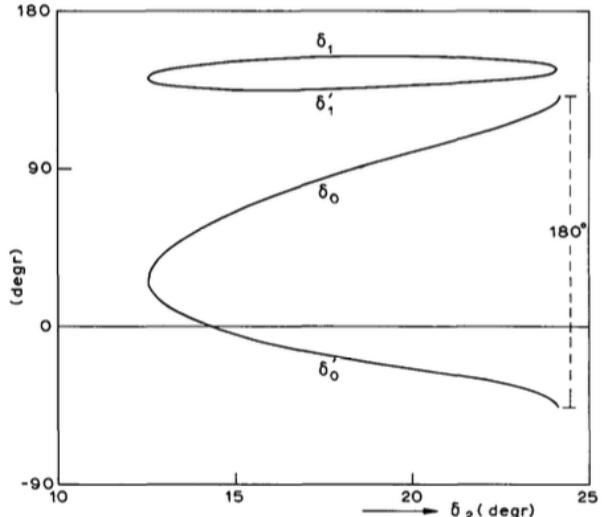
Crichton (1966) found a phase-ambiguous amplitude with only 2 partial waves

$$\delta_2 = \delta'_2 = 20^\circ = 0.349066$$

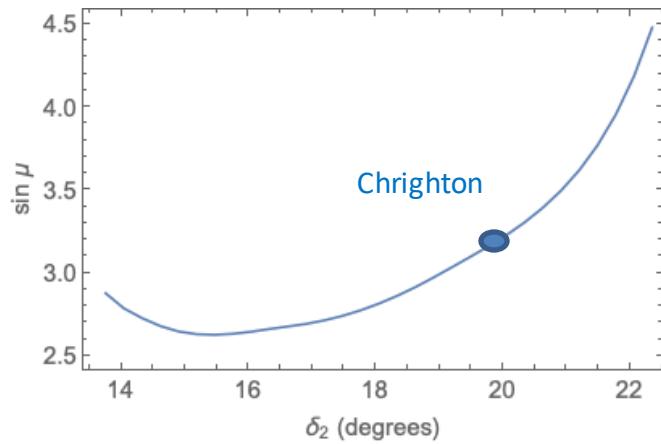
$$\delta_0 = -0.407703, \quad \delta_1 = -0.758247, \quad \delta'_0 = 1.72571 \quad \delta'_1 = -0.463483$$



[Atkinson 1973]  
found a family of solutions



Changing  $\delta_2$  changes  
the solution along a curve [Atkinson 1973]



# Phase ambiguities with ML

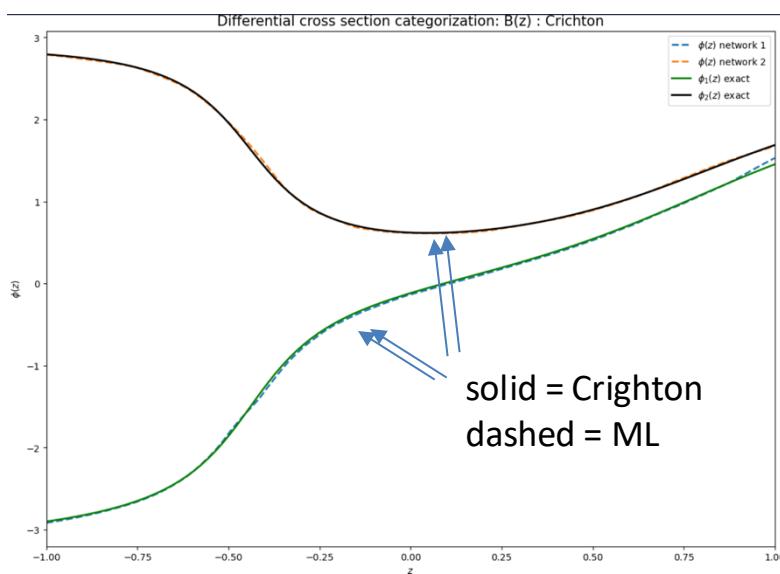
Given  $B(z)$ , find two phases  $\phi_1(z)$  and  $\phi_2(z)$

- Unitarity condition loss for each  $\phi$ :

$$\mathcal{L} = \mathbb{E} \left\| B(z) \sin \phi(z) - \frac{1}{4\pi} \int_{-1}^1 dz_1 \int_0^{2\pi} d\phi_1 B(z_1) B(z_2) \cos(\phi(z_1) - \phi(z_2)) \right\|^2$$

- Add repulsive loss to keep solutions apart

$$\mathcal{L}_R = \mathbb{E}_z \|d(\phi_1(z), \phi_2(z))\|^{-p} + \mathbb{E}_z \|d(\pi - \phi_1(z), \phi_2(z))\|^{-p}$$



- Reduce repulsion to zero to find exact solutions

- Two solutions found with ML agree exactly with Crichton's
- We input  $B(z)$  and find phases

# Machine Learning approach

Atkinson (1977): consider a class of functions based on a single complex number  $z_1$

$$A_1(z) = \frac{z - z_1}{1 - z_1} F(z)$$

$$A_2(z) = \frac{z - z_1^*}{1 - z_1^*} F(z)$$

$$B(z) = |A_1(z)| = |A_2(z)|$$

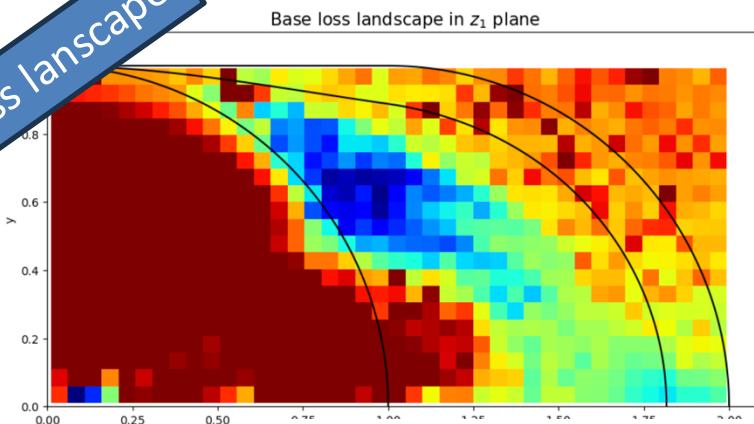
Loss =

unitarity for  $\phi_1$

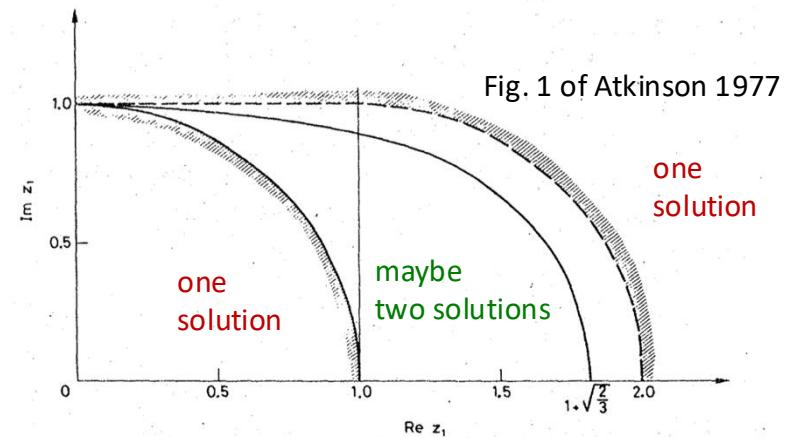
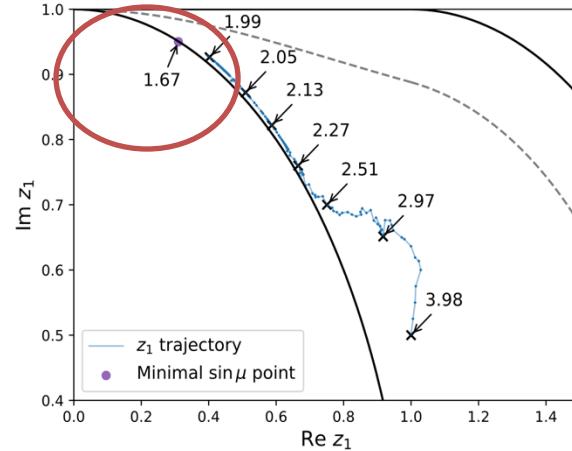
unitarity for  $\phi_2$

$\phi_1$ - $\phi_2$  repulsive term

Loss landscape



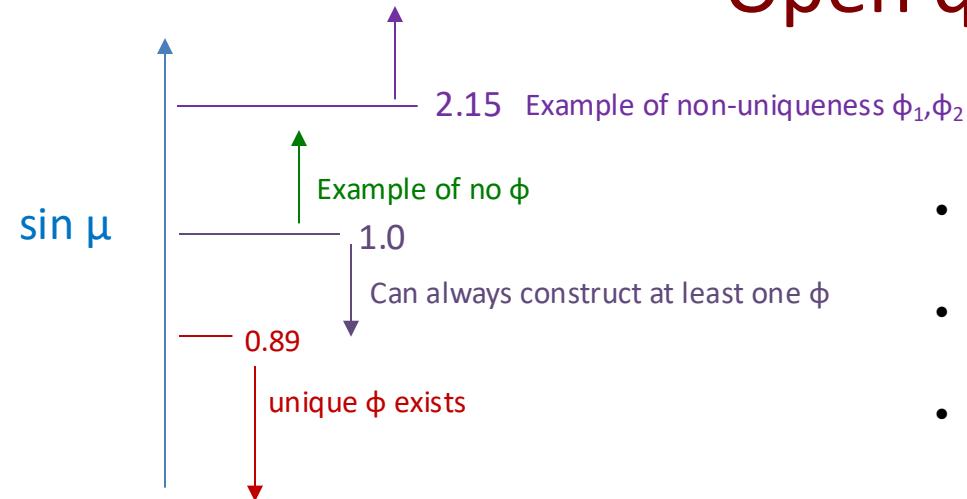
Gradient descent in  $\sin \mu$



First improvement on phase-ambiguity bound in 50 years!

- Crichton (1966),  $\sin \mu = 3.2$
- Atkinson (1977),  $\sin \mu = 2.3$
- MDS et al. (2023),  $\sin \mu = 1.67$

# Open questions

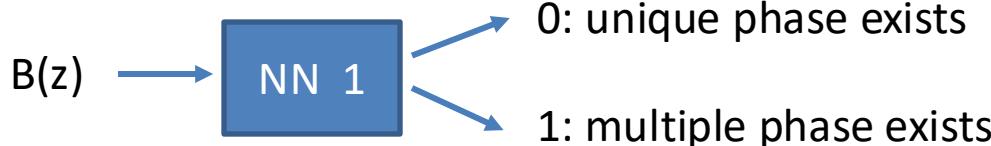


- Can 2.15 be lowered?
  - Yes: to 1.64 at least
- Can 0.89 be raised?
  - Uniqueness proof hard to answer with ML
- How can we construct  $\phi(z)$  given  $B(z)$ 
  - Using ML ✓

## New questions

- What properties do the phase ambiguous solutions have?
- Is there a better way to characterize solutions than  $\sin \mu$ ?

- Train **NN 1**



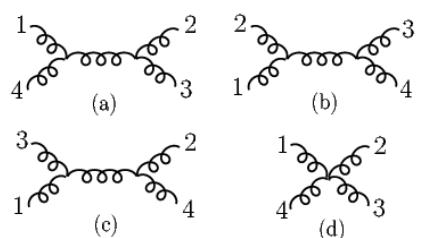
- Train **NN 2** to figure out what **NN 1** is doing
  - Symbolic regression?
  - Can we learn a better indicator for phase determination than  $\sin \mu$ ?

# 2. Spinor-helicity amplitudes

The S matrix is mostly understood perturbatively

calculate some Feynman diagrams for  
4 gluon scattering

get a messy answer



$$\begin{aligned} &= -\frac{\langle 12 \rangle \langle 13 \rangle \langle 24 \rangle [13] [24]}{\langle 23 \rangle \langle 34 \rangle^2 [12] [23]} + \frac{\langle 12 \rangle \langle 13 \rangle \langle 24 \rangle [14]}{\langle 23 \rangle \langle 34 \rangle^2 [12]} - \frac{\langle 12 \rangle \langle 24 \rangle [13] [24]^2}{\langle 34 \rangle^2 [12] [14] [23]} + \frac{\langle 12 \rangle \langle 24 \rangle [24]}{\langle 34 \rangle^2 [12]} + \frac{\langle 12 \rangle [13] [24] [34]}{\langle 34 \rangle [12] [14] [23]} \\ &\quad - \frac{\langle 12 \rangle [34]}{\langle 34 \rangle [12]} - \frac{\langle 13 \rangle \langle 14 \rangle [13] [34]}{\langle 34 \rangle^2 [12] [23]} - \frac{\langle 13 \rangle \langle 24 \rangle [13] [24] [34]}{\langle 34 \rangle^2 [12] [14] [23]} + \frac{\langle 13 \rangle \langle 24 \rangle [34]}{\langle 34 \rangle^2 [12]} - \frac{\langle 13 \rangle \langle 24 \rangle [13] [24]}{\langle 34 \rangle^2 [12]^2} + \frac{\langle 13 \rangle \langle 24 \rangle [14] [23]}{\langle 34 \rangle^2 [12]^2} \\ &\quad + \frac{\langle 13 \rangle [13] [34]^2}{\langle 34 \rangle [12] [14] [23]} - \frac{\langle 14 \rangle \langle 23 \rangle [34]}{\langle 34 \rangle^2 [12]} - \frac{\langle 23 \rangle \langle 24 \rangle [13] [24]^2}{\langle 34 \rangle^2 [12]^2 [14]} + \frac{\langle 23 \rangle \langle 24 \rangle [23] [24]}{\langle 34 \rangle^2 [12]^2} + \frac{\langle 23 \rangle [13] [24] [34]}{\langle 34 \rangle [12]^2 [14]} - \frac{\langle 23 \rangle [23] [34]}{\langle 34 \rangle [12]^2} \end{aligned}$$

simplify!

$$= -\frac{\langle 12 \rangle [34]^2}{\langle 34 \rangle [14] [23]} \quad \text{Parke-Taylor Formula}$$

6-point amplitude

really big mess

(9 pages Parke, Taylor 1985)

Our result has successfully passed both these numerical checks.

Details of the calculation, together with a full exposition of our techniques, will be given in a forthcoming article. Furthermore, we hope to obtain a simple analytic form for the answer, making our result not only an experimentalist's, but also a theorist's delight.

Parke,Taylor (1985)

# Six gluon scattering

Hundreds of Feynman diagrams

Simple !

$$|\mathcal{M}_6(1^-2^-3^+4^+5^+6^+)|^2 = \frac{(p_1 \cdot p_2)^3}{(p_2 \cdot p_3)(p_3 \cdot p_4)(p_4 \cdot p_5)(p_5 \cdot p_6)(p_6 \cdot p_1)}$$

We do not expect such a simple expression for the other helicity amplitudes.  
Also, we challenge the string theorists to prove more rigorously that eqn(3) is correct.

Parke and Taylor (1986)

- simpler form suggests deeper structure
- is there a better way to do the calculation?
  - In this case, yes! (BCFW recursion)



largely inspired the modern amplitudes  
program  
(amplituhedron, tropical geometry, etc.)

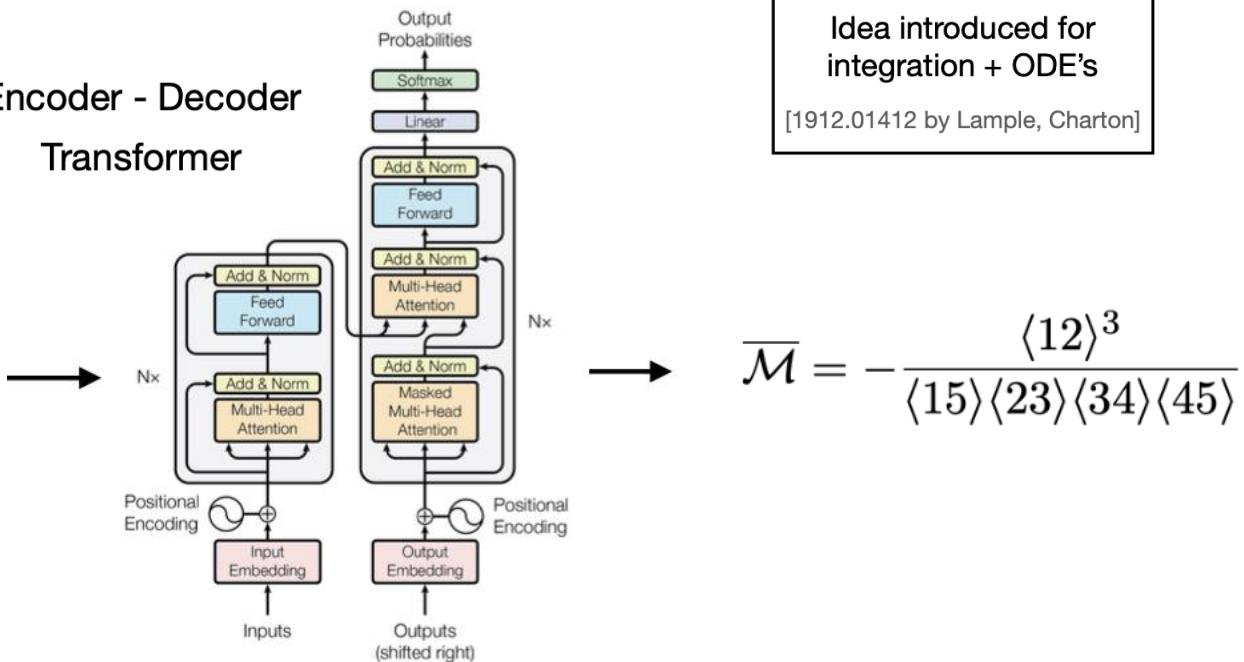
Parke and Taylor saw a pattern

- Then they guessed a simplified form
- That's just what transformers do!

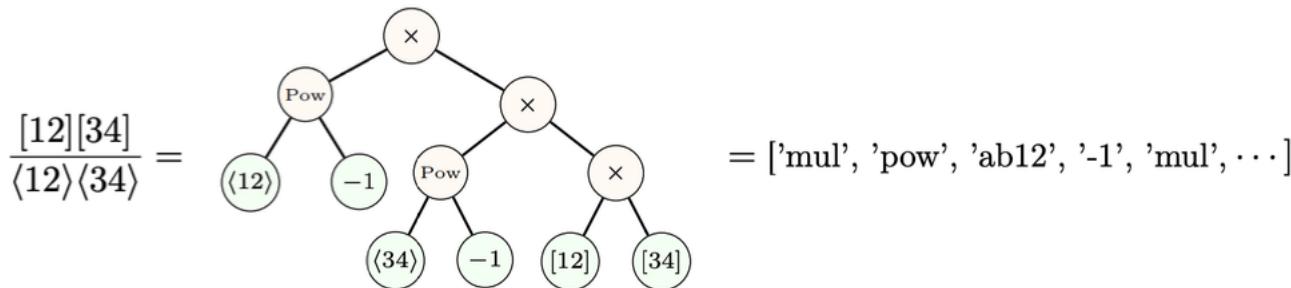
# Simplification with transformers

Encoder - Decoder  
Transformer

$$\mathcal{M} = \frac{\langle 12 \rangle^3 [13]}{\langle 23 \rangle \langle 24 \rangle \langle 35 \rangle \langle 45 \rangle [23]} + \frac{\langle 12 \rangle^3 [14] [25]}{\langle 13 \rangle \langle 24 \rangle \langle 35 \rangle \langle 45 \rangle [12] [45]} \\ - \frac{\langle 12 \rangle^2 [13] [24] [35]}{\langle 24 \rangle \langle 35 \rangle \langle 45 \rangle [12] [23] [45]} + \frac{\langle 12 \rangle^2 [13] [25] [34]}{\langle 24 \rangle \langle 35 \rangle \langle 45 \rangle [12] [23] [45]} \\ - \frac{\langle 12 \rangle^2 [23] [13] [45]}{\langle 15 \rangle \langle 24 \rangle \langle 34 \rangle \langle 35 \rangle [14] [15]} - \frac{\langle 12 \rangle^2 [45]}{\langle 15 \rangle \langle 34 \rangle \langle 35 \rangle [15]}$$



Mathematical expressions are language:



# Generate training data by scrambling

scramble

Input: 
$$\frac{-\langle 34 \rangle^2 [12]^3 [34] [35] + \langle 34 \rangle^2 [12]^2 [13] [23] [45] - \langle 34 \rangle^2 [12]^2 [14] [23] [35]}{\langle 23 \rangle \langle 34 \rangle [13]^2 [34] [35] + \langle 23 \rangle \langle 45 \rangle [13]^2 [35] [45] - \langle 23 \rangle \langle 45 \rangle [13] [14] [35]^2}$$

$[15] \rightarrow \frac{[14][35] - [13][45]}{[34]}$  Schouten

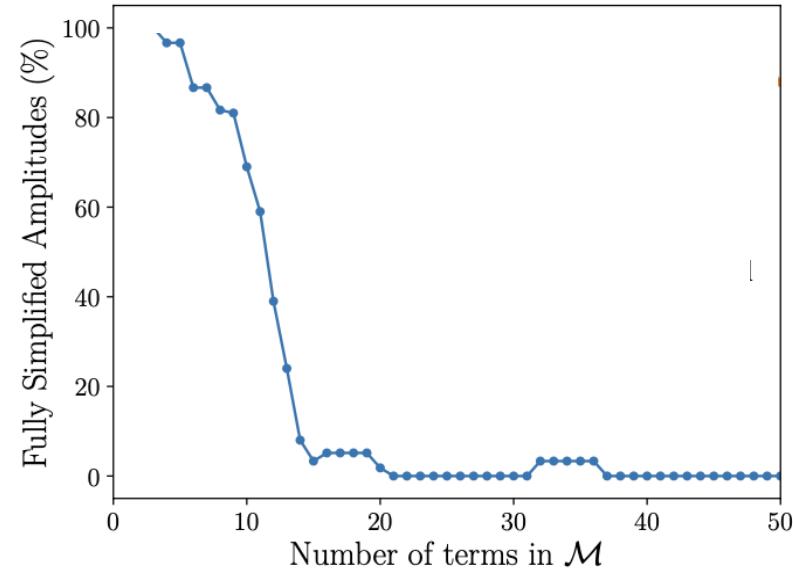
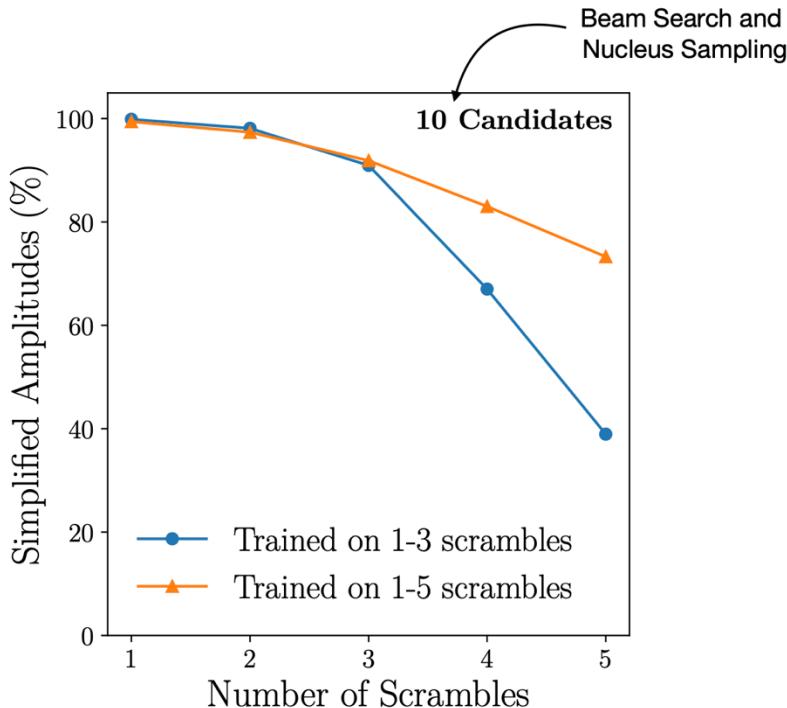
$[25] \rightarrow \frac{[12][35] + [15][23]}{[13]}$  Schouten

$\langle 24 \rangle \rightarrow \frac{\langle 45 \rangle [15] - \langle 34 \rangle [13]}{[12]}$  Momentum conservation

Desired output: 
$$\frac{\langle 34 \rangle^2 [12]^2 [25]}{\langle 23 \rangle \langle 24 \rangle [35]}$$

transformer  
will learn to  
to unscramble  
(translate)

# Transformer performance



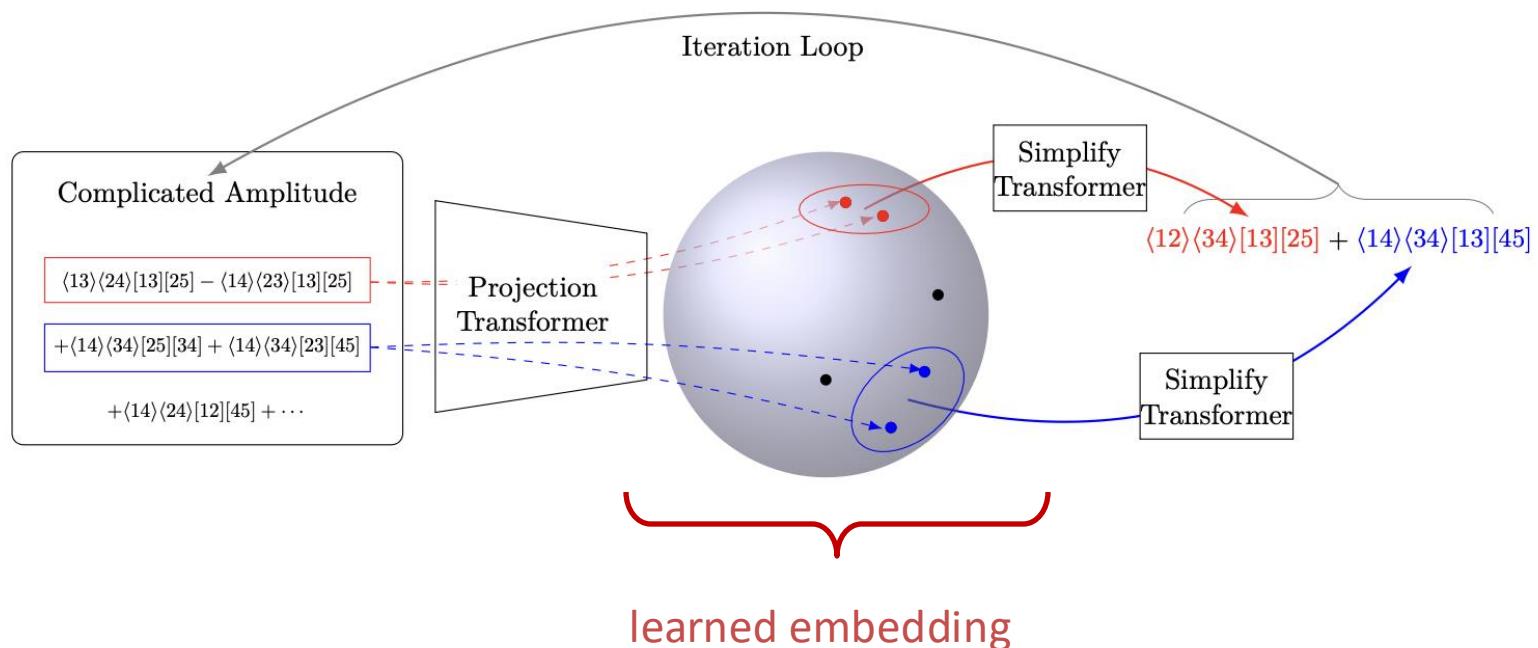
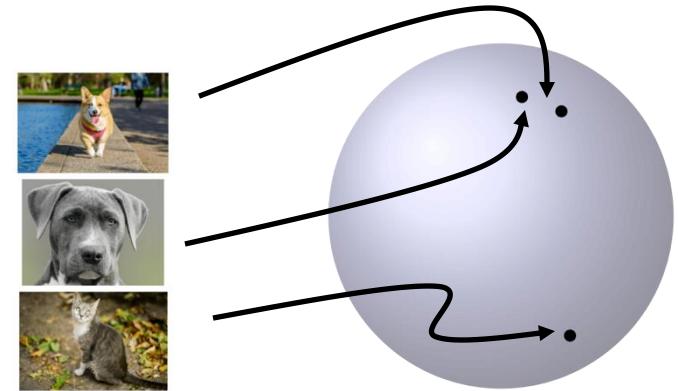
- Does not generalize well
- If trained on 3 scrambles can only unscramble 3 times
- Can't train for  $> 5$  scrambles (exponential amount of training data required)
- Can't simplify expressions more than 15 terms
- Expressions of interest can be very long
  - hundreds of terms
- Need new techniques for organizing transformer
  - We use **contrastive learning**

# Contrastive learning

Learn an embedding so that terms that are **similar** are **close**

- **similar** = appear in some identity
- **close** = metric on embedding space

1. Pick subset of terms expected to simplify
2. Apply transformer
3. Repeat



# Contrastive learning

Supervised contrastive loss

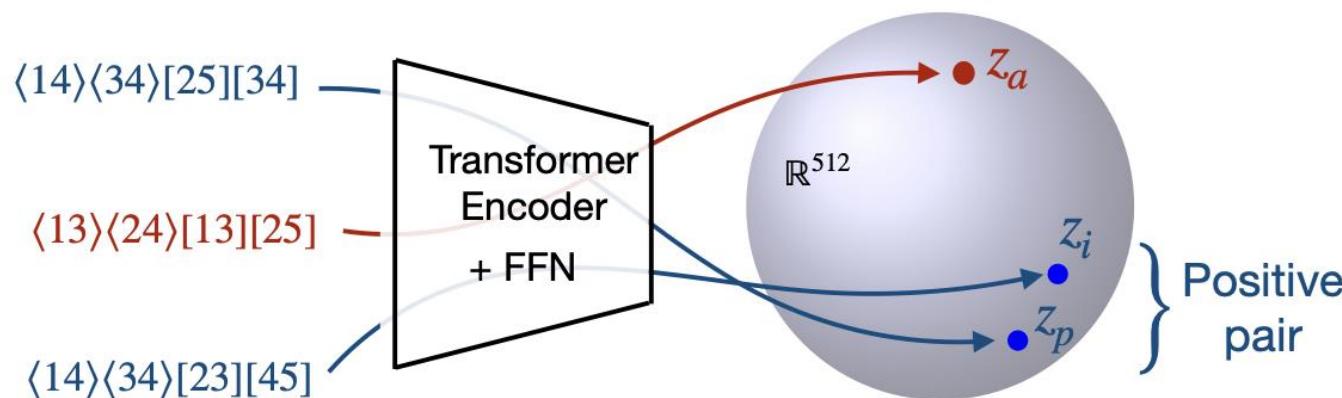
p and i in same identity

$$\mathcal{L}_{\text{con}} = -\frac{1}{|I|} \sum_{i \in I} \frac{1}{|P(i)|} \sum_{p \in P(i)} \log \frac{\exp(s(z_i, z_p)/\tau)}{\sum_{a \in A(i)} \exp(s(z_i, z_a)/\tau)}$$

$s(z_1, z_2) = \frac{z_1 \cdot z_2}{\|z_1\| \|z_2\|}$   
“cosine” similarity

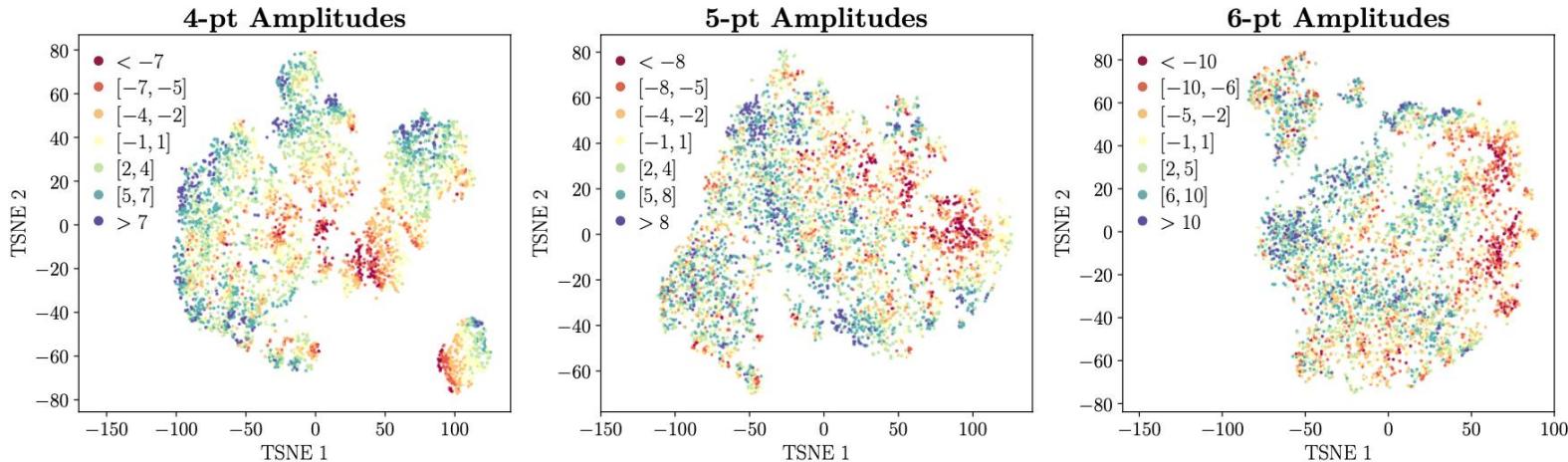
*p and i in same identity*

*a and i not in any identities*



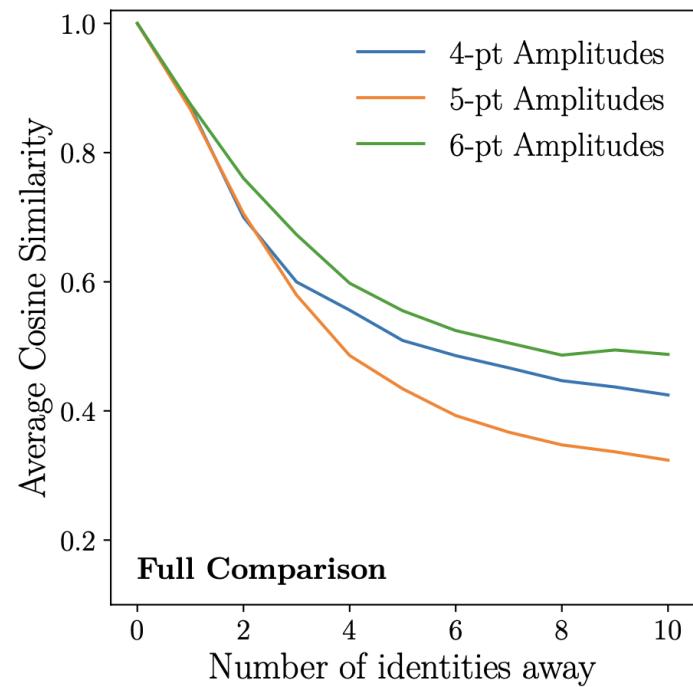
# Cross-checks

- t-SNE on latent space



- color = mass dimension
  - Learns dimensional analysis
  - Learns other features as well

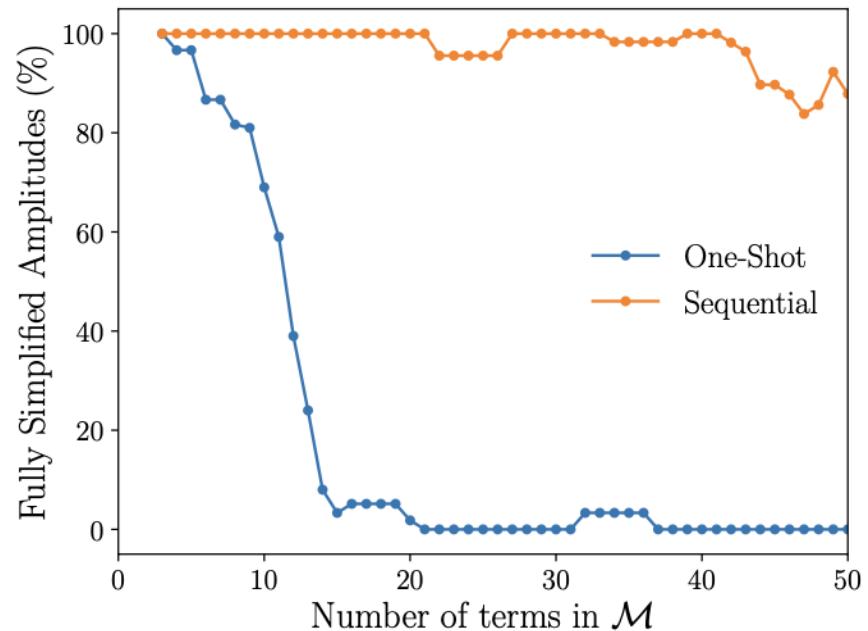
distance inversely  
correlated with complexity



# Performance

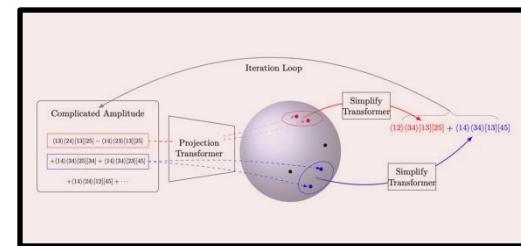
Does it work?

Yes!  
It can simplify long expressions now



# Example application: 5 gluon amplitude

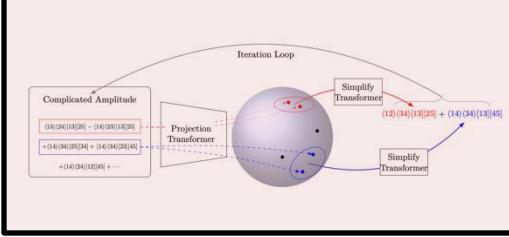
$$\begin{aligned}
& \mathcal{M} = \frac{(12)^3 [13]}{(23)(24)(35)(45)[23]} + \frac{(12)^3 [14][25]}{(13)(24)(35)(45)[12][45]} - \frac{(12)^3 [15][24]}{(13)(24)(35)(45)[12][45]} - \frac{(12)^2 [13][34]}{(24)(35)(45)[14][23]} + \frac{(12)^2 [13]}{(24)(35)(45)[12]} \\
& - \frac{(12)^2 [13][24][35]}{(24)(35)(45)[12][23][45]} + \frac{(12)^2 [13][25][34]}{(24)(35)(45)[12][23][45]} + \frac{(12)^2 [14][35]}{(24)(35)(45)[12][45]} - \frac{(12)^2 [15][34]}{(24)(35)(45)[12][45]} - \frac{(12)^2 [13][45]}{(23)(24)(35)[12][23]} \\
& - \frac{(12)^2 [23][13][45]}{(15)(24)(34)(35)[14][15]} - \frac{(12)^2 [45]}{(15)(34)(35)[15]} - \frac{(12)^2 [13][34][45]}{(15)(24)(35)[14][15][23]} + \frac{(12)^2 [13][45]}{(15)(24)(35)[12][15]} + \frac{(12)^2 [14][45]}{(15)(23)(34)(35)[12][15]} \\
& + \frac{(12)^2 [34][13][34][45]}{(15)(23)(24)(35)[12][15][23]} - \frac{(12)^2 [15][15]}{(13)(24)(35)(45)[12][23]} + \frac{(12)^2 [23][23]}{(13)(24)(35)(45)[12][23]} - \frac{(12)^2 [23][25][34]}{(13)(24)(35)(45)[12][23][45]} \\
& + \frac{(12)^2 [23][25][34][45]}{(13)(24)(35)(45)[12][14][45]} + \frac{(12)^2 [23][14][23][25]}{(13)(24)(35)(45)[12][24][45]} - \frac{(12)^2 [23][15][23][24]}{(13)(24)(35)(45)[12][24][45]} - \frac{(12)^2 [23][25]}{(13)(24)(35)(45)[12][24][45]} \\
& + \frac{(12)^2 [23][15][24]}{(13)(24)(34)(35)[12][14]} + \frac{(12)^2 [24]}{(13)(35)(45)[12]} + \frac{(12)^2 [34][13][24][34]}{(13)(24)(35)(45)[12][14][23]} - \frac{(12)^2 [45]}{(13)(24)(35)[12]} + \frac{(12)^2 [23][13][24][45]}{(13)(15)(24)(35)[12][14][15]} \\
& + \frac{(12)^2 [24][45]}{(13)(15)(32)[15]} + \frac{(12)^2 [34][13][24][45]}{(13)(15)(24)(35)[12][14][15][23]} - \frac{(12)[13][34][35]}{(24)(35)(45)[12][23][45]} + \frac{(12)[13][15][34][35]}{(24)(35)(45)[12][14][23][45]} \\
& + \frac{(12)[13][23][13][34]}{(15)(24)(34)(35)[12][14]} + \frac{(12)[13][34]}{(15)(34)(35)[12]} + \frac{(12)[13][13][34]^2}{(15)(24)(35)[12][14][23]} + \frac{(12)[14][23][13][45]}{(15)(24)(34)(35)[12][15]} \\
& + \frac{(12)[14][45]}{(15)(34)[12][15]} + \frac{(12)[14][13][34][45]}{(15)(24)(35)[12][15][23]} - \frac{(12)[15][13][15][34]}{(24)(35)(45)[12][14][23][23]} + \frac{(12)[23][13][24][34][35]}{(24)(35)(45)[12][14][23][45]} \\
& - \frac{(12)[23][34][35]}{(24)(35)(45)[12][45]} + \frac{(12)[23][13][34]^2}{(24)(35)(45)[12][14][45]} - \frac{(12)[23][13][24][35]}{(24)(35)(45)[12][24][45]} + \frac{(12)[23][14][23][35]}{(24)(35)(45)[12][24][45]} \\
& - \frac{(12)[23][35]}{(24)(34)(35)[12]} + \frac{(12)[23][15][34]}{(24)(34)(35)[12][14]} + \frac{(12)[34]}{(35)(45)[12]} + \frac{(12)[34][13][34]^2}{(24)(35)(45)[12][14][23]} - \frac{(12)[23][2][13][23][45]}{(15)(24)(34)(35)[12][14][15]} \\
& + \frac{(12)[23]^2 [13][24][35]}{(15)(24)(34)(35)[12][14][15]} - \frac{(12)[23][23][45]}{(15)(34)(35)[12][15]} + \frac{(12)[23][24][35]}{(15)(24)(35)[12][15]} + \frac{(12)[23][13][24][34][35]}{(15)(24)(35)[12][14][15][23]} \\
& + \frac{(12)[23][45][13][45]^2}{(15)(24)(34)(35)[12][14][15]} + \frac{(12)[34][45]}{(15)(35)[12][15]} + \frac{(12)[45][45]^2}{(15)(34)(35)[12][15]} + \frac{(12)[34][13][34]^2[45]}{(15)(24)(35)[12][14][15][23]} \\
& + \frac{(12)[45][13][34][45]^2}{(15)(24)(35)[12][14][15][23]} + \frac{(12)[14][23][13][24][34]}{(13)(24)(35)(45)[12][14][23]} - \frac{(12)[14][23][34]}{(13)(24)(35)(45)[12][14][23]} - \frac{(12)[14][23][45]}{(13)(24)(34)(35)[12][15]} \\
& + \frac{(12)[14][23][14][25]}{(13)(24)(34)(35)[12]^2} - \frac{(12)[14][23][15][24]}{(13)(24)(34)(35)[12]^2} + \frac{(12)[14][23][3][13][24][45]}{(13)(15)(24)(34)(35)[12][14][15]} + \frac{(12)[14][23][24][45]}{(13)(15)(34)(35)[12][15]} \\
& + \frac{(12)[14][23][13][24][45]}{(13)(15)(24)(35)[12][14][15][23]} - \frac{(12)[15][23][15][24]}{(13)(24)(35)(45)[12][14][23]} + \frac{(12)[23][2][23]^2}{(13)(24)(35)(45)[12][14][23]} - \frac{(12)[23][2][23][25][34]}{(13)(24)(35)(45)[12][14][23][45]} \\
& + \frac{(12)[23]^2 [15][23][24][34]}{(13)(24)(35)(45)[12][14][23]} - \frac{(12)[23]^2 [23][25]}{(13)(24)(34)(35)[12]^2} + \frac{(12)[23]^2 [15][23][24]}{(13)(24)(34)(35)[12]^2[14]} + \frac{(12)[23][23][24]}{(13)(35)(45)[12]^2} \\
& + \frac{(12)[23][34][13][24][34]}{(13)(24)(35)(45)[12][14][23]} + \frac{(12)[23][13][24][45]}{(13)(24)(35)[12]^2[14]} - \frac{(12)[23][23][45]}{(13)(24)(35)[12]^2} + \frac{(12)[23][25][34]}{(13)(24)(35)[12]^2} - \frac{(12)[23][15][24][34]}{(13)(24)(35)[12]^2} \\
& + \frac{(12)[23][45][25][45]}{(13)(24)(34)(35)[12]^2} - \frac{(12)[23][45][15][24][45]}{(13)(24)(34)(35)[12][14][23]} + \frac{(13)[23][13][34]^2[35]}{(24)(35)(45)[12][14][23][45]} + \frac{(13)[23][2][13][34][35]}{(15)(24)(34)(35)[12][14][15]} \\
& + \frac{(13)[23][34][35]}{(15)(34)(35)[12][15]} + \frac{(13)[23][13][34]^2[35]}{(15)(24)(35)[12][14][15][23]} + \frac{(14)[23][13][34]^2}{(24)(35)(45)[12][14][15][23]} + \frac{(14)[23][2][13][34][45]}{(15)(24)(34)(35)[12][14][15]} \\
& + \frac{(14)[23][34][45]}{(15)(34)(35)[12][15]} + \frac{(14)[23][13][34]^2[45]}{(15)(24)(35)[12][14][15][23]} - \frac{(15)[23][13][35]}{(24)(34)(35)[12]^2} + \frac{(23)^2 [13][24][34][35]}{(24)(35)(45)[12][14][15][45]} \\
& - \frac{(23)^2 [23][34][35]}{(24)(35)(45)[12][24][45]} + \frac{(23)^2 [13][24][35]}{(24)(34)(35)[12][24][45]} + \frac{(23)[24][35]}{(34)(35)[12]^2} + \frac{(23)[34][35]}{(24)(35)[12]^2} - \frac{(14)[15][23][15][45]}{(13)(24)(34)(35)[12][24][45]} \\
& + \frac{(14)[23]^2 [13][24][34]}{(13)(24)(35)(45)[12][14][15]} - \frac{(14)[23]^2 [23][34]}{(13)(24)(35)(45)[12]^2} + \frac{(14)[23]^2 [13][24][45]}{(13)(24)(34)(35)[12][14][15]} + \frac{(14)[23][24][45]}{(13)(34)(35)[12]^2} + \frac{(14)[23][34][45]}{(13)(24)(35)[12]^2}
\end{aligned}$$



$$\overline{\mathcal{M}} = - \frac{\langle 12 \rangle^3}{\langle 15 \rangle \langle 23 \rangle \langle 34 \rangle \langle 45 \rangle}$$

# Example application: graviton-scalar scattering

298 terms



simplifies to 2 terms

$$\overline{\mathcal{M}} = \frac{\langle 12 \rangle \langle 13 \rangle \langle 23 \rangle}{\langle 24 \rangle \langle 25 \rangle \langle 45 \rangle} \left( \frac{[14][35]}{\langle 14 \rangle \langle 35 \rangle} - \frac{[15][34]}{\langle 15 \rangle \langle 34 \rangle} \right)$$

# Try it yourself!

<https://spinorhelicity.streamlit.app/>

Sampling Method

Nucleus Sampling

Beam Search

Greedy Decoding

---

Beam Size (Beam Search and Nucleus Sampling)

5

Nucleus Cutoff (Nucleus Sampling)

0.95

Temperature (Nucleus Sampling)

1.50

## Spinor-Helicity Simplification

This app simplifies spinor-helicity expressions. Enter the input in the syntax of Fortran ( $ab(1,2)**2*sb(1,2)$ ), Mathematica ( $ab[1,2]^2*sb[1,2]$ ), or S@M ( $Spaa[1,2]^2*Spbb[1,2]$ ). All terms should have uniform scaling in mass dimension and little group, with purely monomial denominators. Specify the number of external particles and the mode of simplification, with additional tunable parameters on the sidebar. One-shot and iterative mode are effective for shorter (<10 terms) and longer (<40 terms) expressions, respectively. Apply even longer expressions at your own risk. See [our paper](#) for details.

For faster performance we encourage a local download from this [GitHub repository](#).

For any inquiries or further information, please contact [Aurélien Dersy](#).

Amplitude Type

5-pt

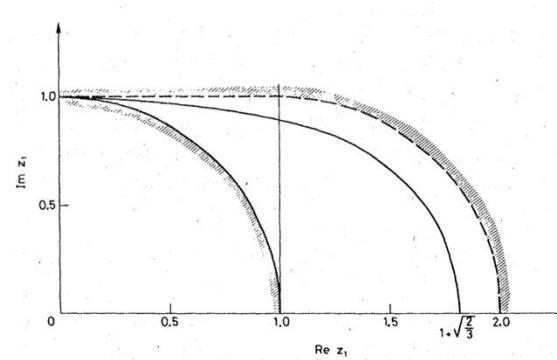
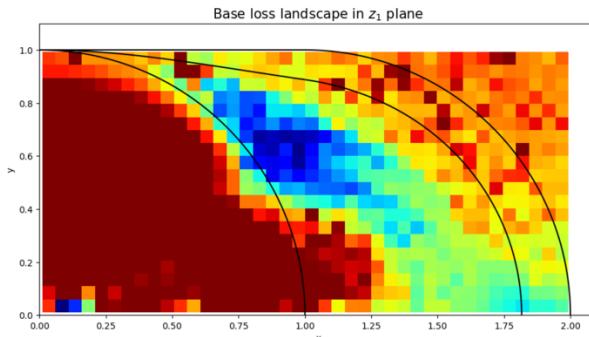
Input Equation

$$(-ab(1,2)**2*sb(1,2)*sb(1,5)-ab(1,3)*ab(2,4)*sb(1,3)*sb(4,5)+ab(1,3)*ab(2,4)*sb(1,4)*sb(3,5)-ab(1,3)*ab(2,4)*sb(1,5)-ab(1,3)*ab(2,5)*sb(1,4)+ab(1,3)*ab(2,5)*sb(1,4)-ab(1,3)*ab(2,5)*sb(1,5)-ab(1,3)*ab(2,5)*sb(1,6)+ab(1,3)*ab(2,5)*sb(1,7)-ab(1,3)*ab(2,5)*sb(1,8)-ab(1,3)*ab(2,5)*sb(1,9)-ab(1,3)*ab(2,5)*sb(1,10)-ab(1,3)*ab(2,5)*sb(1,11)-ab(1,3)*ab(2,5)*sb(1,12)-ab(1,3)*ab(2,5)*sb(1,13)-ab(1,3)*ab(2,5)*sb(1,14)-ab(1,3)*ab(2,5)*sb(1,15)-ab(1,3)*ab(2,5)*sb(1,16)-ab(1,3)*ab(2,5)*sb(1,17)-ab(1,3)*ab(2,5)*sb(1,18)-ab(1,3)*ab(2,5)*sb(1,19)-ab(1,3)*ab(2,5)*sb(1,20)-ab(1,3)*ab(2,5)*sb(1,21)-ab(1,3)*ab(2,5)*sb(1,22)-ab(1,3)*ab(2,5)*sb(1,23)-ab(1,3)*ab(2,5)*sb(1,24)-ab(1,3)*ab(2,5)*sb(1,25)-ab(1,3)*ab(2,5)*sb(1,26)-ab(1,3)*ab(2,5)*sb(1,27)-ab(1,3)*ab(2,5)*sb(1,28)-ab(1,3)*ab(2,5)*sb(1,29)-ab(1,3)*ab(2,5)*sb(1,30)-ab(1,3)*ab(2,5)*sb(1,31)-ab(1,3)*ab(2,5)*sb(1,32)-ab(1,3)*ab(2,5)*sb(1,33)-ab(1,3)*ab(2,5)*sb(1,34)-ab(1,3)*ab(2,5)*sb(1,35)-ab(1,3)*ab(2,5)*sb(1,36)-ab(1,3)*ab(2,5)*sb(1,37)-ab(1,3)*ab(2,5)*sb(1,38)-ab(1,3)*ab(2,5)*sb(1,39)-ab(1,3)*ab(2,5)*sb(1,40)-ab(1,3)*ab(2,5)*sb(1,41)-ab(1,3)*ab(2,5)*sb(1,42)-ab(1,3)*ab(2,5)*sb(1,43)-ab(1,3)*ab(2,5)*sb(1,44)-ab(1,3)*ab(2,5)*sb(1,45))$$

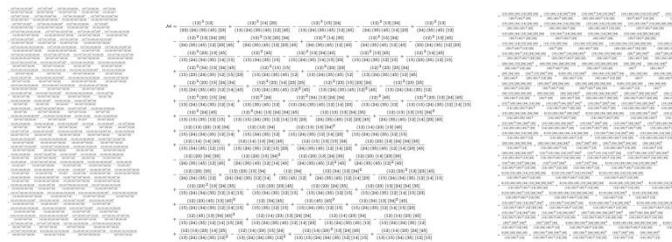
$$-\langle 12 \rangle^3 [12] [15] - \langle 12 \rangle \langle 13 \rangle \langle 24 \rangle [13] [45] + \langle 12 \rangle \langle 13 \rangle \langle 24 \rangle [14] [35] - \langle 12 \rangle \langle 13 \rangle \langle 24 \rangle [15] [34] \\ \langle 15 \rangle \langle 23 \rangle \langle 34 \rangle \langle 45 \rangle [12] [15]$$

# Conclusions

- Machine learning is a powerful tool to understand the S-matrix
  - New results on old non-perturbative S-matrix questions



- Simplification of perturbative expressions



$$\frac{\langle 12 \rangle^3}{\langle 15 \rangle \langle 23 \rangle \langle 34 \rangle \langle 45 \rangle}$$

- Future of ML in high energy theory is symbolic
  - Lots to do!