LORENTZ-EQUIVARIANT GEOMETRIC ALGEBRA TRANSFORMERS FOR HIGH-ENERGY PHYSICS

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MACHINE LEARNING APPROACHES FOR HIGH ENERGY PHYSICS

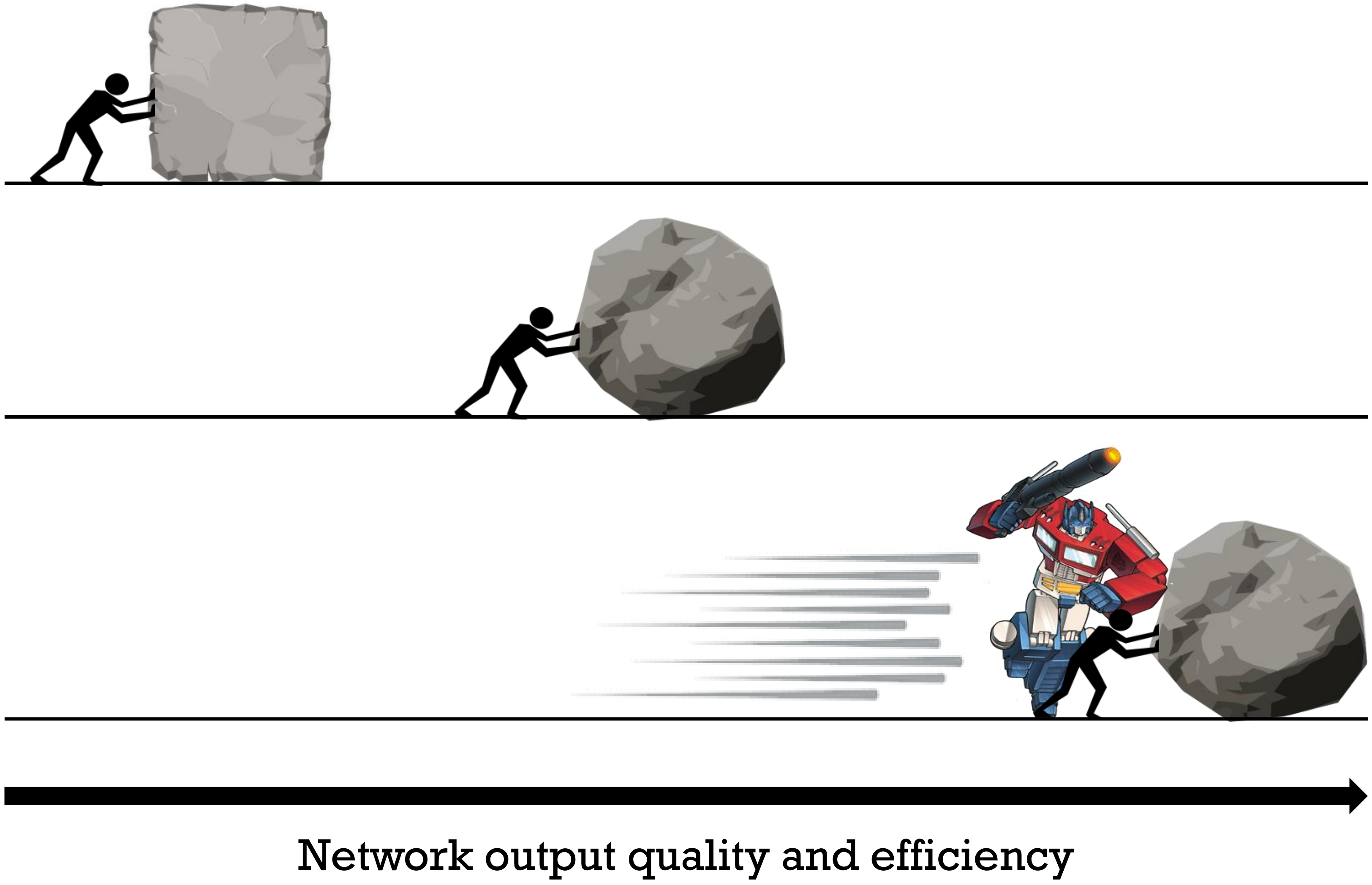
Out of the box model

+

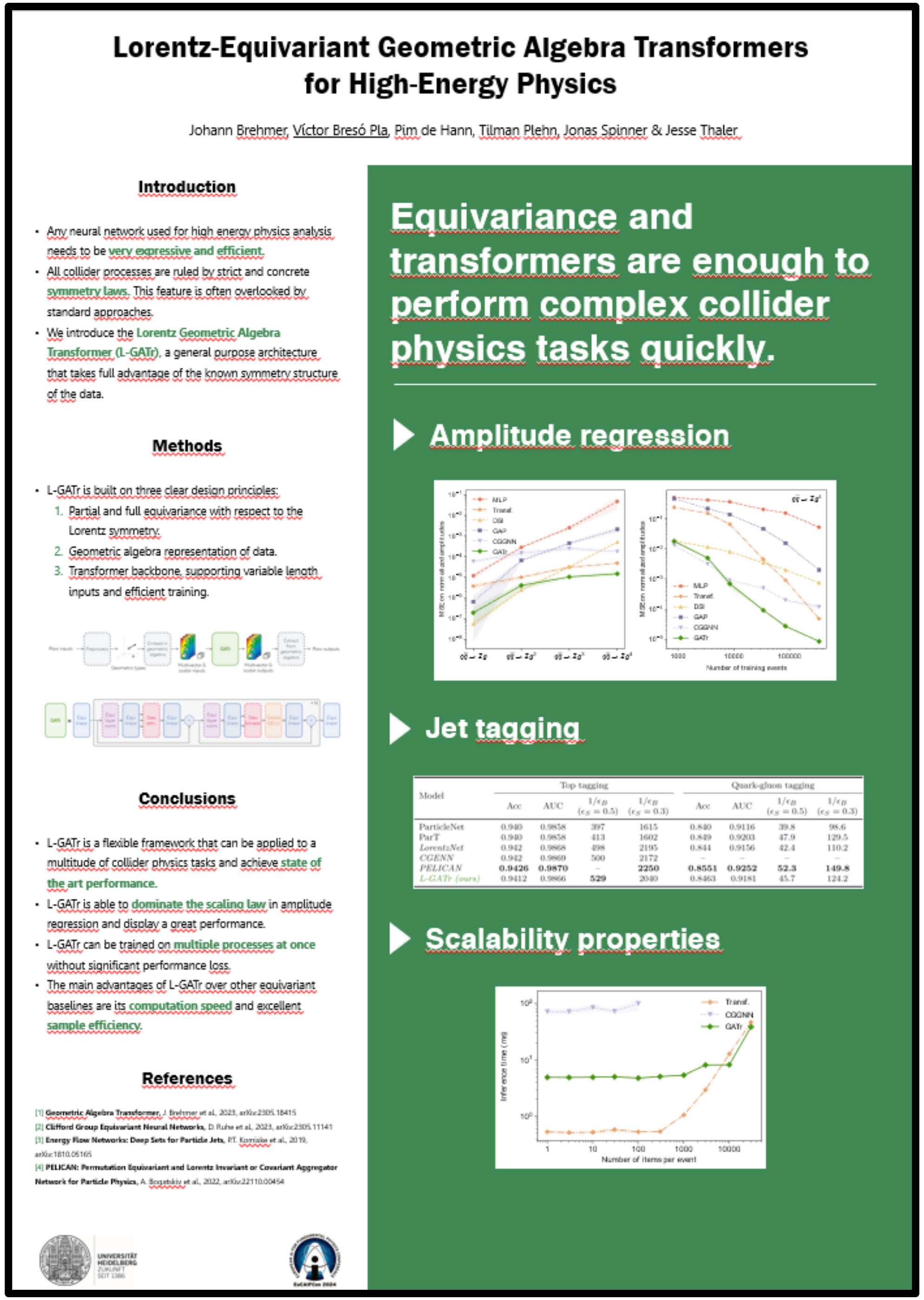
Symmetry awareness

+

Transformer backbone



- Introducing the **Lorentz Geometric Algebra Transformer (L-GATr)**
- Main results:
  1. We achieve **state of the art performance** for multiple collider physics tasks
  2. L-GATr can learn the features of **multiple processes simulatenously**
  3. L-GATr is **faster** and more **memory efficient** than other equivariant baselines



Lorentz-Equivariant Geometric Algebra Transformers for High-Energy Physics

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Introduction

- Any neural network used for high energy physics analysis needs to be **very expressive and efficient.**
- All collider processes are ruled by strict and concrete **symmetry laws.** This feature is often overlooked by standard approaches.
- We introduce the **Lorentz Geometric Algebra Transformer (L-GATr)**, a general purpose architecture that takes full advantage of the known symmetry structure of the data.

Methods

- L-GATr is built on three clear design principles:
  1. Partial and full equivariance with respect to the Lorentz symmetry.
  2. Geometric algebra representation of data.
  3. Transformer backbone, supporting variable length inputs and efficient training.

Conclusions

- L-GATr is a flexible framework that can be applied to a multitude of collider physics tasks and achieve **state of the art performance.**
- L-GATr is able to **dominate the scaling law** in amplitude regression and display a great performance.
- L-GATr can be trained on **multiple processes at once** without significant performance loss.
- The main advantages of L-GATr over other equivariant baselines are its **computation speed** and excellent **sample efficiency.**

References

[1] **Geometric Algebra Transformer,** J. Brehmer et al., 2023, arXiv:2305.18415

[2] **Clifford Group Equivariant Neural Networks,** D. Ruhe et al., 2023, arXiv:2305.11141

[3] **Energy Flow Networks: Deep Sets for Particle Jets,** P.T. Komiske et al., 2019, arXiv:1810.05165

[4] **PELICAN: Permutation Equivariant and Lorentz Invariant or Covariant Aggregator Network for Particle Physics,** A. Bogatskiy et al., 2022, arXiv:2211.00454

Equivariance and transformers are enough to perform complex collider physics tasks quickly.

Amplitude regression

Jet tagging

Model	Top tagging				Quark-gluon tagging			
	Acc	AUC	$1/\epsilon_B$ ($\epsilon_S = 0.5$)	$1/\epsilon_B$ ($\epsilon_S = 0.3$)	Acc	AUC	$1/\epsilon_B$ ($\epsilon_S = 0.5$)	$1/\epsilon_B$ ($\epsilon_S = 0.3$)
ParticleNet	0.940	0.9858	397	1615	0.840	0.9116	39.8	98.6
ParT	0.940	0.9858	413	1602	0.849	0.9203	47.9	129.5
LorentzNet	0.942	0.9868	498	2195	0.844	0.9156	42.4	110.2
CGENN	0.942	0.9869	500	2172	–	–	–	–
PELICAN	**0.9426**	**0.9870**	–	**2250**	**0.8551**	**0.9252**	**52.3**	**149.8**
L-GATr (ours)	0.9412	0.9866	**529**	2040	0.8463	0.9181	45.7	124.2

Scalability properties