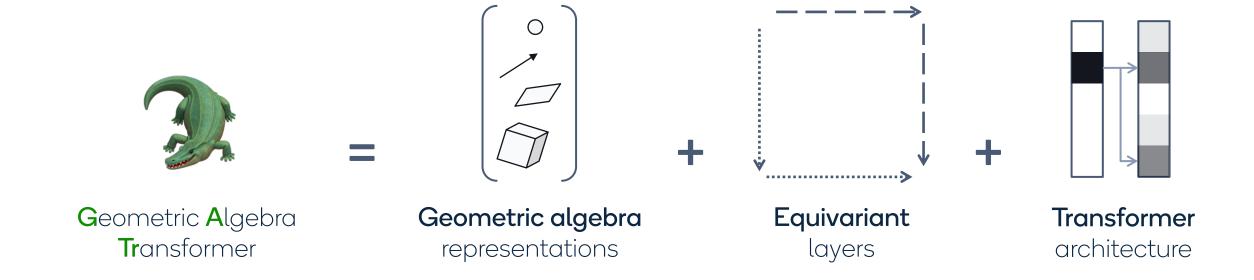


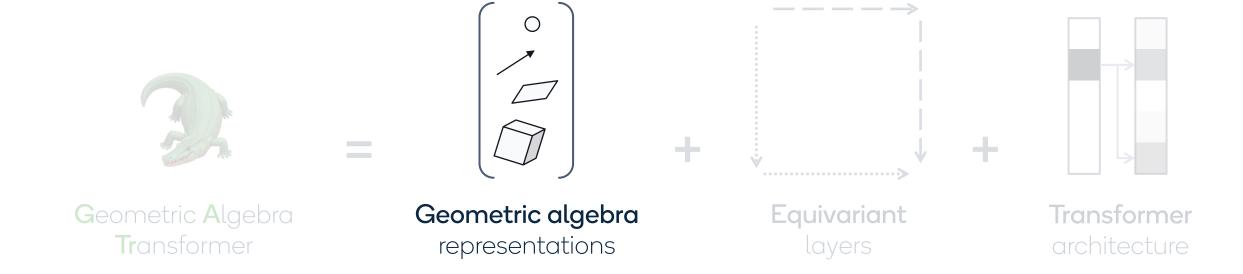
Geometric Algebra Transformers

Johann Brehmer Pim de Haan Sönke Behrends Taco Cohen Qualcomm Technologies Netherlands B. V.



Geometric Algebra Transformer a universal architecture for geometric data





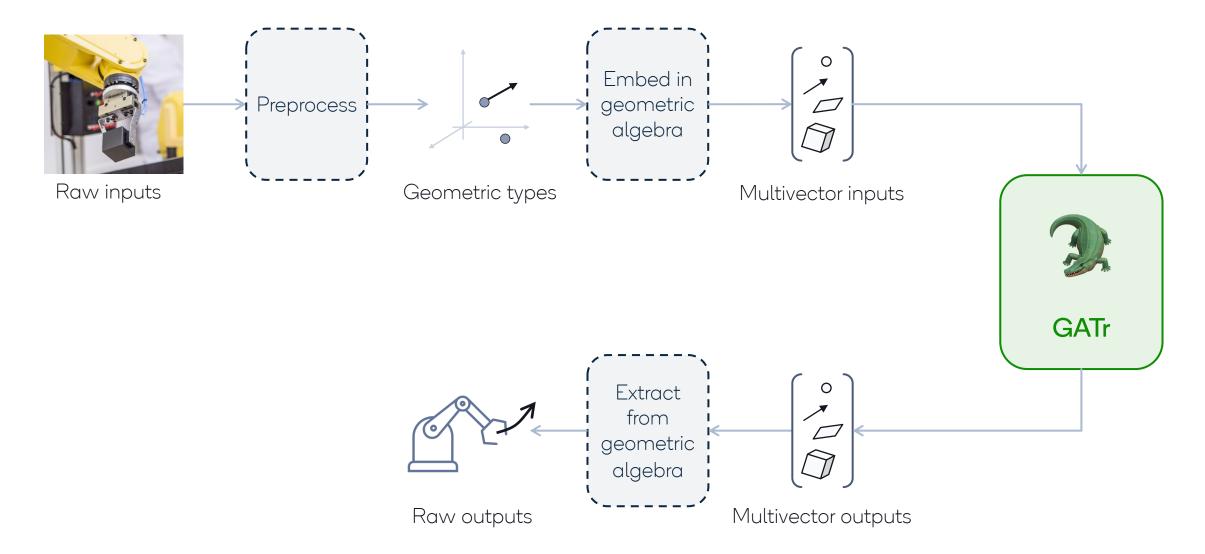
Geometric algebra:

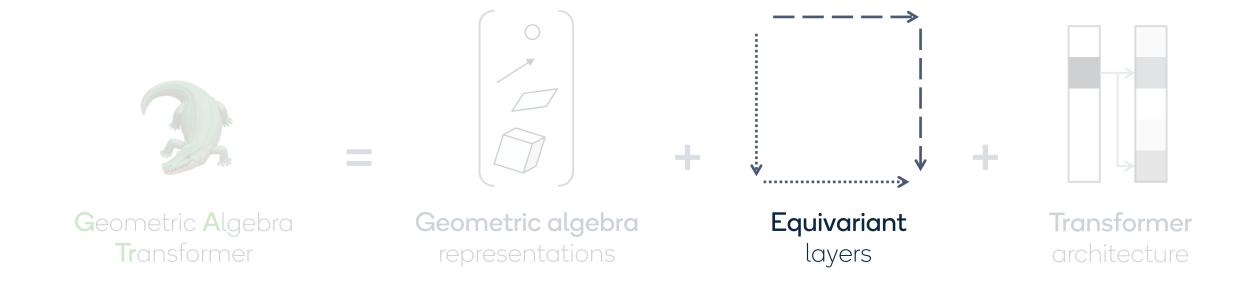
- Multivectors, a **16-dimensional representation** of 3D geometric data
- "Typing": a point is not a direction of movement is not the orientation of a plane
- A dictionary for representations of common objects and transformations

Object / operator	Scalar	Vector		Bivector		Trivector		PS
	1	e_0	e_i	e_{0i}	e_{ij}	e_{0ij}	e_{123}	e_{0123}
Scalar $\lambda \in \mathbb{R}$	λ	0	0	0	0	0	0	0
Plane w/ normal $n \in \mathbb{R}^3$, origin shift $d \in \mathbb{R}$	0	d	n	0	0	0	0	0
Line w/ direction $n \in \mathbb{R}^3$, orthogonal shift $s \in \mathbb{R}^3$	0	0	0	s	n	0	0	0
Point $p \in \mathbb{R}^3$	0	0	0	0	0	p	1	0
Pseudoscalar $\mu \in \mathbb{R}$	0	0	0	0	0	0	0	μ
Reflection through plane w/ normal $n \in \mathbb{R}^3$, origin shift $d \in \mathbb{R}$	0	d	n	0	0	0	0	0
Translation $t \in \mathbb{R}^3$	1	0	0	$\frac{1}{2}t$	0	0	0	0
Rotation expressed as quaternion $q \in \mathbb{R}^4$	q_0	0	0	0	q_i	0	0	0
Point reflection through $p \in \mathbb{R}^3$	0	0	0	0	0	p	1	0

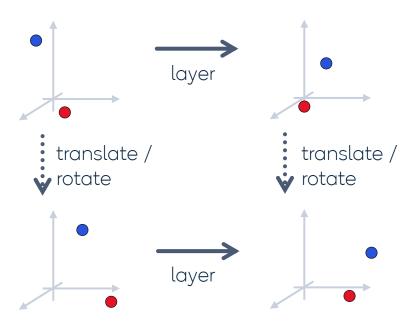
• Canonical operations on these representations

Geometric algebra representations in practice



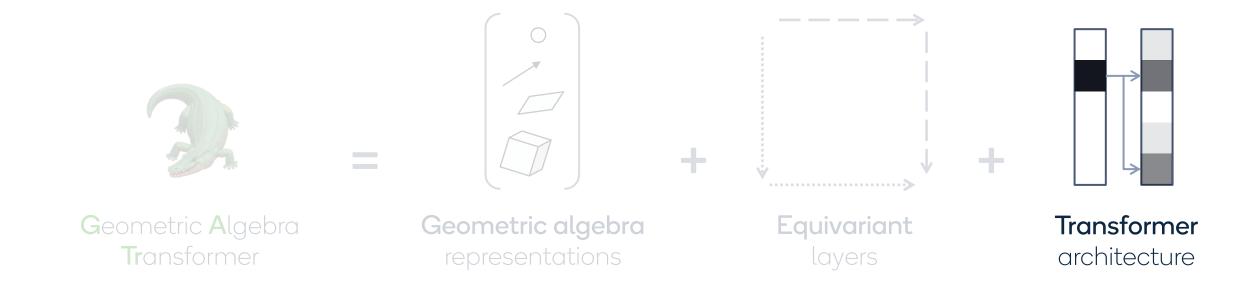


Guiding principle: E(3) equivariance



We design equivariant...

- Linear layers
- Nonlinearities and normalization layers
- Geometric layers
- Attention mechanisms

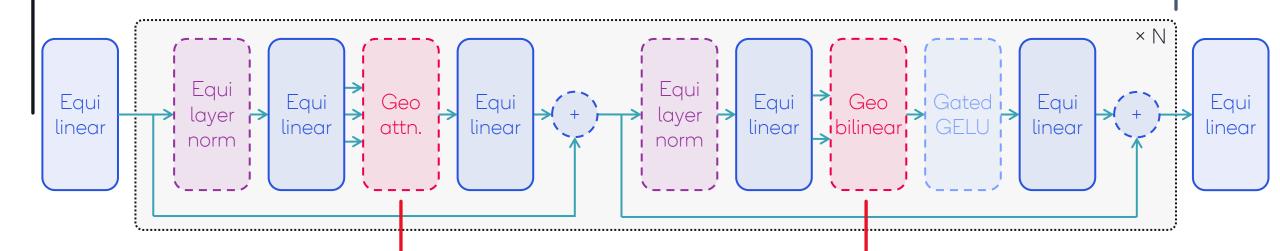


Input and output data

can have one or multiple token dimensions

Attention blocks

can be stacked to large depth, gradients are propagated efficiently

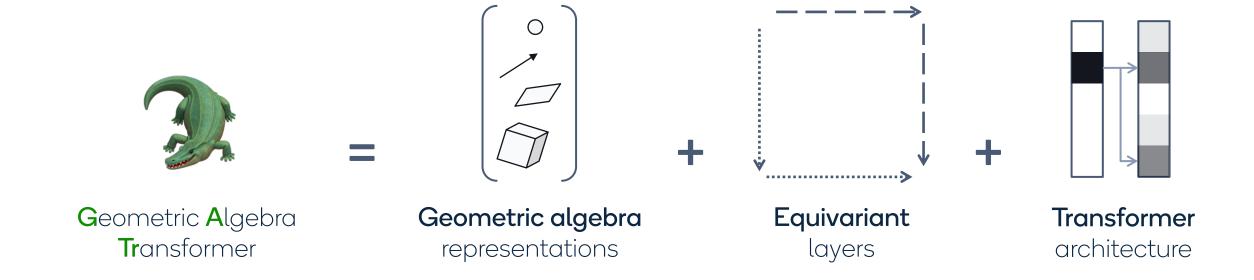


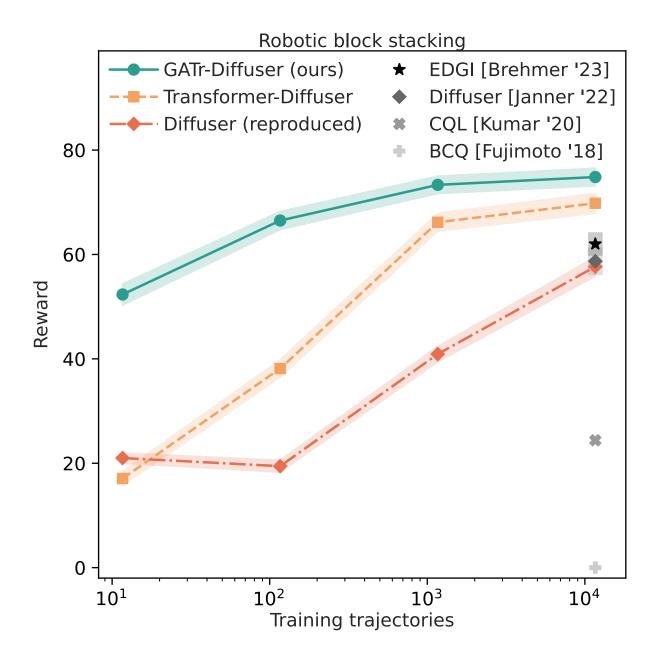
Geometric attention

generalizes scaled dotproduct attention

Geometric bilinears

allow for construction of new geometric types





Robotic block stacking task [Janner et al, ICML 2022]:

GATr outperforms all baselines with 1% of the training data

Related and concurrent:

arXiv:2305.11141

Clifford Group Equivariant Neural Networks

David Ruhe

AI4Science Lab, AMLab, API University of Amsterdam david.ruhe@gmail.com

Johannes Brandstetter

Microsoft Research AI4Science johannesb@microsoft.com

Patrick Forré

AI4Science Lab, AMLab University of Amsterdam p.d.forre@uva.nl

Abstract

We introduce Clifford Group Equivariant Neural Networks: a novel approach for constructing $\mathrm{E}(n)$ -equivariant networks. We identify and study the *Clifford group*, a subgroup inside the Clifford algebra, whose definition we slightly adjust to achieve several favorable properties. Primarily, the group's action forms an orthogonal automorphism that extends beyond the typical vector space to the entire Clifford algebra while respecting the multivector grading. This leads to several non-equivalent subrepresentations corresponding to the multivector decomposition. Furthermore, we prove that the action respects not just the vector space structure of

Geometric Algebra

Transformer

Geometric Algebra Transformers

Johann Brehmer Pim de Haan Sönke Behrends Taco Cohen
Qualcomm AI Research*
{jbrehmer, pim, sbehrend, tacos}@qti.qualcomm.com

Abstract

Problems involving geometric data arise in a variety of fields, including computer vision, robotics, chemistry, and physics. Such data can take numerous forms, such as points, direction vectors, planes, or transformations, but to date there is no single architecture that can be applied to such a wide variety of geometric types while respecting their symmetries. In this paper we introduce the Geometric Algebra Transformer (GATr), a general-purpose architecture for geometric data. GATr represents inputs, outputs, and hidden states in the projective geometric algebra, which offers an efficient 16-dimensional vector space representation of common geometric objects as well as operators acting on them. GATr is equivariant with respect to E(3), the symmetry group of 3D Euclidean space. As a transformer, GATr is scalable, expressive, and versatile. In experiments with n-body modeling and robotic planning, GATr shows strong improvements over non-geometric baselines.

1 Introduction

From molecular dynamics to astrophysics, from material design to robotics, fields across science and engineering deal with geometric data: points, directions, surfaces, orientations, and so on. The geometric nature of data provides a rich structure: a notion of common operations between geometric types (computing distances between points, applying rotations to orientations, etc.), a well-defined behaviour of data under transformations of a system, and the independence of certain properties of coordinate system choices.

When learning relations from geometric data, incorporating this rich structure into the architecture

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