TRAJECTORY PREDICTION USING EQUIVARIANT CONTINUOUS CONVOLUTION

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Paper under double-blind review

ABSTRACT

Trajectory prediction is a critical part of many AI applications, for example, the safe operation of autonomous vehicles. However, current methods are prone to making inconsistent and physically unrealistic predictions. We leverage insights from fluid dynamics to overcome this limitation by considering internal symmetry in trajectories. We propose a novel model, **E**quivariant **C**ontinous **CO**nvolution (ECCO) for improved trajectory prediction. ECCO uses rotationally-equivariant continuous convolutions to embed the symmetries of the system. On two real-world vehicle and pedestrian trajectory datasets, ECCO attains competitive accuracy with significantly fewer parameters. It is also more sample efficient, generalizing automatically from few data points in any orientation. Lastly, ECCO improves generalization with equivariance, resulting in more physically consistent predictions. Our method provides a fresh perspective towards increasing trust and transparency in deep learning models.

1 INTRODUCTION

Trajectory prediction is one of the core tasks in AI, from the movement of basketball players to fluid particles to car traffic (Sanchez-Gonzalez et al., 2020; Gao et al., 2020; Shah & Romijnders, 2016). A common abstraction underlying these tasks is the movement of many interacting agents, analogous to a many-particle system. Therefore, understanding the states of these particles, their dynamics, and hidden interactions is critical to accurate and robust trajectory forecasting.

Even for purely physical systems such as particle physics, the complex interactions among large number of particles makes this a difficult problem. For vehicle or pedestrian trajectories, this challenge is further compounded with latent factors such as human psychology. Given these difficulties, current approaches require large amounts of training data and many parameters in the model. State-of-the-art methods in this domain such as Gao et al. (2020) are based on graph neural networks. They do not exploit the physical properties of system and often make predictions which are not self-consistent or physically meaningful. Furthermore, they predict a single agent trajectory at a time instead of multiple agents simultaneously.

Our model is built upon a key insight of many-particle systems pertaining to intricate internal symmetry. Consider a model which predicts the trajectory of cars on a road. To be successful, such a model must understand the physical behavior of vehicles together with human psychology. It should distinguish left from right turns, and give consistent outputs for intersections rotated with different orientation. As shown in Figure 1, a driver's velocity rotates with the entire scene, whereas vehicle interactions are invariant to such a rotation. Likewise, psychological factors such as reaction speed or attention may be considered vectors with prescribed transformation properties.

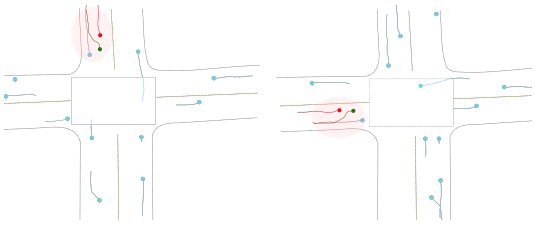

Figure 1: Car trajectories in two scenes. Though the entire scenes are not related by a rotation, the circled areas are. ECCO exploits this symmetry to improve generalization and sample efficiency.

In this paper, we propose an equivariant continuous convolutional model, ECCO, for trajectory forecasting. Continuous convolution generalizes discrete convolution and is adapted to data in many-particle systems with complex local interactions. Ummenhofer et al. (2019) designed a model using continuous convolutions for particle-based fluid simulations. Meanwhile, equivariance to group symmetries has proven to be a powerful tool to integrate physical intuition in physical science applications (Wang et al., 2020; Brown & Lunter, 2019; Kanwar et al., 2020). Here, we test the hypothesis that an equivariant model can also capture internal symmetry in non-physical human behavior. Our model utilizes a novel weight sharing scheme, torus kernels, and is rotationally equivariant.

We evaluate our model on two real-world trajectory datasets: Argoverse autonomous vehicle dataset (Chang et al., 2019) and TrajNet++ pedestrian trajectory forecasting challenge (Kothari et al., 2020). We demonstrate on par or better prediction accuracy to baseline models with fewer parameters, better sample efficiency, and stronger generalization properties. Lastly, we demonstrate theoretically and experimentally that our polar coordinate-indexed filters have lower equivariance discretization error due to being better adapted to the symmetry group.

Our main contributions are as follows:

- We propose **E**quivariant **C**ontinous **CO**nvolution (ECCO), a rotationally equivariant deep neural network that can capture internal symmetry in trajectories.
- We design ECCO using a novel weight sharing scheme based on orbit decomposition and polar coordinate-indexed filters. We implement equivariance for both the standard and regular representation $L^2(\mathrm{SO}(2))$.
- On benchmark Argoverse and TrajNet++ datasets, ECCO demonstrates comparable accuracy while enjoying better generalization, fewer parameters, and better sample complexity.

2 Related Work

Trajectory Forecasting For vehicle trajectories, classic models in transportation include the Car-Following model (Pipes, 1966) and Intelligent Driver model (Kesting et al., 2010). Deep learning has also received considerable attention; for example, Liang et al. (2020) and Gao et al. (2020) use graph neural networks to predict vehicle trajectories. Djuric et al. (2018) use rasterizations of the scene with CNN. See the review paper by Veres & Moussa (2019) for deep learning in transportation. For human trajectory modeling, Alahi et al. (2016) propose Social LSTM to learn these human-human interactions. TrajNet (Sadeghian et al., 2018) and TrajNet++ (Kothari et al., 2020) introduce benchmarking for human trajectory forecasting. We refer readers to Rudenko et al. (2020) for a comprehensive survey. Nevertheless, many deep learning models are data-driven. They require large amounts of data, have many parameters, and can generate physically inconsistent predictions.

Continuous Convolution Continuous convolutions over point clouds (CtsConv) have been successfully applied to classification and segmentation tasks (Wang et al., 2018; Lei et al., 2019; Xu et al., 2018; Wu et al., 2019; Su et al., 2018; Li et al., 2018; Hermosilla et al., 2018; Atzmon et al., 2018; Hua et al., 2018). More recently, a few works have used continuous convolution for modeling trajectories or flows. For instance, Wang et al. (2018) uses CtsConv for inferring flow on LIDAR data. Schenck & Fox (2018) and Ummenhofer et al. (2019) model fluid simulation using `CtsConv`. Closely related to our work is Ummenhofer et al. (2019), who design a continuous convolution network for particle-based fluid simulations. However, they use a ball-to-sphere mapping which is not well-adapted for rotational equivariance and only encode 3 frames of input. Graph neural networks (GNNs) are a related strategy which have been used for modeling particle system dynamics (Sanchez-Gonzalez et al., 2020). GNNs are also permutation invariant, but they do not natively encode relative positions and local interaction as a CtsConv-based network does.

Equivariant and Invariant Deep Learning Developing neural nets that preserve symmetries has been a fundamental task in image recognition (Cohen et al., 2019b; Weiler & Cesa, 2019; Cohen & Welling, 2016a; Chidester et al., 2018; Lenc & Vedaldi, 2015; Kondor & Trivedi, 2018; Bao & Song, 2019; Worrall et al., 2017; Cohen & Welling, 2016b; Weiler et al., 2018; Dieleman et al., 2016; Maron et al., 2020). Equivariant networks have also been used to predict dynamics: for example, Wang et al. (2020) predicts fluid flow using Galilean equivariance but only for gridded data. Fuchs et al. (2020) use $\mathrm{SE}(3)$-equivariant transformers to predict trajectories for a small number of particles as a regression task. As in this paper, both Bekkers (2020) and Finzi et al. (2020) address the challenge of parameterizing a kernel over continuous Lie groups. Finzi et al. (2020) apply

their method to trajectory prediction on point clouds using a small number of points following strict physical laws. Worrall et al. (2017) also parameterizes convolutional kernels using polar coordinates, but maps these onto a rectilinear grid for application to image data. Thomas et al. (2018) introduce Tensor Field Networks which are $\mathrm{SO}(3)$-equivariant continuous convolutions. Unlike our work, both Worrall et al. (2017) and Thomas et al. (2018) define their kernels using harmonic functions.

3 BACKGROUND

We first review the necessary background of continuous convolution and rotational equivariance.

3.1 CONTINUOUS CONVOLUTION

Continuous convolution generalizes the discrete convolution to point clouds. Let $\mathbf{f}^{(i)} \in \mathbb{R}^{c_{\text{in}}}$ denote the feature vector of particle i. Thus $\mathbf{f}$ is a vector field which assigns to the points $\mathbf{x}^{(i)}$ a vector in $\mathbb{R}^{c_{\text{in}}}$. The kernel of the convolution $K\colon \mathbb{R}^2 \to \mathbb{R}^{c_{\text{out}} \times c_{\text{in}}}$ is a *matrix* field: for each point $\mathbf{x} \in \mathbb{R}^2$, $K(\mathbf{x})$ is a $c_{\text{out}} \times c_{\text{in}}$ matrix. Let a be a radial local attention map with $a(r) = 0$ for $r > R$. Define the output feature vector $\mathbf{g}^{(i)}$ of particle i by

$$\mathbf{g}^{(i)} = \texttt{CtsConv}_{K,R}(\mathbf{x}, \mathbf{f}; \mathbf{x}^{(i)}) = \sum_j a(\|\mathbf{x}^{(j)} - \mathbf{x}^{(i)}\|) K(\mathbf{x}^{(j)} - \mathbf{x}^{(i)}) \cdot \mathbf{f}^{(j)}. \tag{1}$$

We omit the attention normalization term of Ummenhofer et al. (2019). `CtsConv` is naturally equivariant to permutation of labels and translation invariant.

3.2 ROTATIONAL EQUIVARIANCE

Continuous convolution is not naturally rotationally equivariant. Fortunately, we can translate the technique of rotational equivariance on CNNs to continuous convolutions.

More precisely, denote the symmetry group of 2D rotations by $\mathrm{SO}(2) = \{\mathrm{Rot}_\theta : 0 \leq \theta < 2\pi\}$. It has a topological structure with underlying manifold the circle S^1. The group $\mathrm{SO}(2)$ can act on a vector space $\mathbb{R}^c$ by specifying a representation map $\rho\colon \mathrm{SO}(2) \to \mathrm{GL}(\mathbb{R}^c)$ which assigns to each element of $\mathrm{SO}(2)$ an invertible $c \times c$ matrix. For example, the *standard representation* ρ_1 on $\mathbb{R}^2$ is by 2×2 rotation matrices. The *regular representation* ρ_{reg} on $L^2(\mathrm{SO}(2)) = \{\varphi : \mathrm{SO}(2) \to \mathbb{R} : |\varphi|^2 \text{ is integrable}\}$ is $\rho_{\text{reg}}(\mathrm{Rot}_\phi)(\varphi) = \varphi \circ \mathrm{Rot}_{-\phi}$. Given input $\mathbf{f}$ with representation ρ_{in} and output with representation ρ_{out}, a map F is $\mathrm{SO}(2)$-equivariant if

$$F(\rho_{\text{in}}(\mathrm{Rot}_\theta)\mathbf{f}) = \rho_{\text{out}}(\mathrm{Rot}_\theta) F(\mathbf{f}).$$

4 ECCO: TRAJECTORY PREDICTION USING ROTATIONALLY EQUIVARIANT CONTINUOUS CONVOLUTION

In trajectory prediction, given historical position and velocity data of n particles over t_{in} timesteps, we want to predict their positions over the next t_{out} timesteps. Denote the ground truth dynamics as ξ, which maps $\xi(\mathbf{x}_{t-t_{\text{in}}:t}, \mathbf{v}_{t-t_{\text{in}}:t}) = \mathbf{x}_{t:t+t_{\text{out}}}$. Motivated by the observation in Figure 1, we wish to learn a model f that approximates the dynamics while preserving the internal symmetry, specifically rotational equivariance.

We introduce ECCO, a model for trajectory prediction based on rotationally equivariant continuous convolution. We implement rotationally equivariant continuous convolutions using a weight sharing scheme based on orbit decomposition. We also describe equivariant per-particle linear layers which are a special case of continuous convolution with radius $R = 0$ analogous to 1x1 convolutions in CNNs. Such layers are useful for passing information between layers from each particle to itself.

4.1 ECCO MODEL OVERVIEW

The high-level architecture of ECCO is illustrated in Figure 2. It is important to remember that the input, output, and hidden layers are all vector fields over the particles. For one dataset, there is also

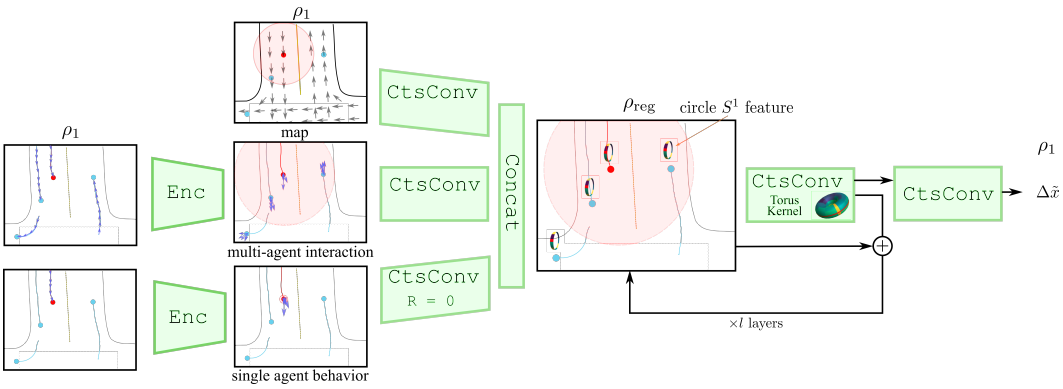

Figure 2: Overview of model architecture. Past velocities are aggregated by an encoder `Enc`. Together with map information this is then encoded by 3 `CtsConv`s into ρ_{reg} features. Then $l+1$ `CtsConv` layers are used to predict $\Delta\tilde{x}$. The predicted position $\hat{x}_{t+1} = \Delta\tilde{x} + \tilde{x}$ where $\tilde{x}$ is a numerically extrapolated using velocity and accleration. Since $\Delta\tilde{x}$ is translation invariant, $\hat{x}$ is equivariant.

environmental information available in the form of road lane markers. Denote marker positions by $\mathbf{x}_{\text{map}}$ and direction vectors by $\mathbf{v}_{\text{map}}$. This data is thus also a particle field, but static.

To design an equivariant network, one must choose the group representation. This choice plays an important role in shaping the learned hidden states. We focus on two representations of $\text{SO}(2)$: ρ_1 and ρ_{reg}. The representation ρ_1 is that of our input features, and ρ_{reg} is for the hidden layers. For ρ_1, we constrain the kernel in Equation 1. For ρ_{reg}, we further introduce a new operator, convolution with torus kernels.

In order to make continuous convolution rotationally equivariant, we translate the general constraint for discrete CNNs developed in Weiler & Cesa (2019) to continuous convolution. Let $\mathbb{R}^{c_{\text{out}}}$ and $\mathbb{R}^{c_{\text{in}}}$ be $\text{SO}(2)$-representations ρ_{out} and ρ_{in} respectively, then we require

$$K(\theta + \phi, r) = \rho_{\text{out}}(\text{Rot}_\theta) K(\phi, r) \rho_{\text{in}}(\text{Rot}_\theta^{-1}). \tag{2}$$

Imposing such a constraint for continuous convolution requires us to develop an efficient weight sharing scheme for the kernels $K(\theta, r)$, which solve Equation 2.

4.2 Weight Sharing by Orbits and Stabilizers.

Given a point $\mathbf{x} \in \mathbb{R}^2$ and a group G, the set $O_{\mathbf{x}} = \{g\mathbf{x} : g \in G\}$ is the *orbit* of the point $\mathbf{x}$. The set of orbits gives a partition of $\mathbb{R}^2$ into the origin and circles of radius $r > 0$. The set of group elements $G_{\mathbf{x}} = \{g : g\mathbf{x} = x\}$ fixing $\mathbf{x}$ is called the *stabilizer* of the point $\mathbf{x}$. We use the orbits and stabilizers to constrain the weights of K. Simply put, we share weights across orbits and constrain weights according to stabilizers, as shown in Figure 3-Left.

The ray $D = \{(0, r) : r \geq 0\}$ is a *fundamental domain* for the action of $G = \text{SO}(2)$ on base space $\mathbb{R}^2$. That is, D contains exactly one point from each orbit. We first define $K(0, r)$ for each $(0, r) \in D$. Then we obtain $K(\theta, r)$ from $K(0, r)$ by setting $\phi = 0$ in Equation 2 as such

$$K(\theta, r) = \rho_{\text{out}}(\text{Rot}_\theta) K(0, r) \rho_{\text{in}}(\text{Rot}_\theta^{-1}). \tag{3}$$

For $r > 0$, the group acts *freely* on $(0, r)$, i.e. the stabilizer contains only the identity. This means that Equation 2 imposes no additional constraints on $K(0, r)$. Thus $K(0, r) \in \mathbb{R}^{c_{\text{out}} \times c_{\text{in}}}$ is a matrix of freely learnable weights.

For $r = 0$, however, the orbit $O_{(0,0)}$ is only one point. The stabilizer of $(0, 0)$ is all of G, which requires

$$K(0, 0) = \rho_{\text{out}}(\text{Rot}_\theta) K(0, 0) \rho_{\text{in}}(\text{Rot}_\theta^{-1}) \text{ for all } \theta. \tag{4}$$

Thus $K(0, 0)$ is an equivariant per-particle linear map $\rho_{\text{in}} \to \rho_{\text{out}}$.

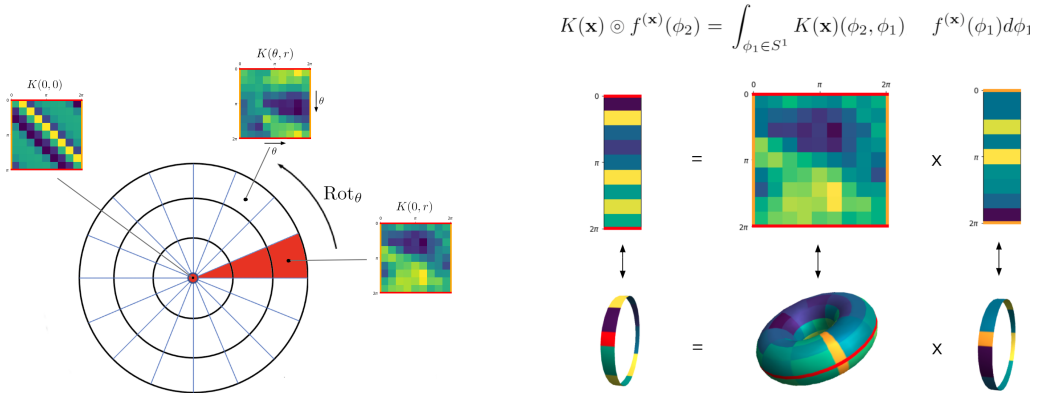

Figure 3: Left: A torus kernel field K from a ρ_{reg}-field to a ρ_{reg}-field. The kernel is itself a field: at each point $\mathbf{x}$ in space the kernel $K(\mathbf{x})$ yields a different matrix. The matrices along the red sector are freely trainable. The matrices at all white sectors are determined by those in the red sector according to the circular shifting rule illustrated above. The matrix at the red bullseye is trainable but constrained to be circulant, i.e. preserved by the circular shifting rule. Right: The torus kernel acts on features which are functions on the circle. By cutting open the torus and features along the reg and orange lines we can identify the operation at each point with matrix multiplication.

We can analytically solve Eqn. (4) for $K(0,0)$ using representation theory. Table 1 shows the unique solutions for different combinations of ρ_1 and ρ_{reg}. For details see subsection A.2.

Table 1: Equivariant linear maps for $K(0,0)$. Trainable weights are $c \in \mathbb{R}$ and $\kappa\colon S^1 \to \mathbb{R}$, where S^1 is the manifold underlying $\mathrm{SO}(2)$.

ρ_{in}	$\rho_{\text{out}} = \rho_1$	$\rho_{\text{out}} = \rho_{\text{reg}}$
ρ_1	$(a, b) \mapsto (ca, cb)$	$ca\cos(\theta) + cb\sin(\theta)$
ρ_{reg}	$\mathbf{f} \mapsto c \begin{pmatrix} \int_{S^1} \mathbf{f}(\theta)\cos(\theta)d\theta \\ \int_{S^1} \mathbf{f}(\theta)\sin(\theta)d\theta \end{pmatrix}$	$\int_{S^1} \kappa(\theta - \phi)\mathbf{f}(\phi)d\phi$

Note that 2D and 3D rotation equivariant continuous convolutions are implemented in Worrall et al. (2017) and Thomas et al. (2018) respectively. They both use harmonic functions which require expensive evaluation of analytic functions at each point. Instead, we provide a simpler solution. We require only knowledge of the orbits, stabilizers, and input/output representations. Additionally, we bypass Clebsch-Gordon decomposition used in Thomas et al. (2018) by mapping directly between the representations in our network. Next, we describe an efficient implementation of equivariant continuous convolution.

4.3 Polar Coordinate Kernels

Rotational equivariance informs our kernel discretization and implementation. We store the kernel K of continuous convolution as a 4-dimensional tensor by discretizing the domain. Specifically, we discretize $\mathbb{R}^2$ using polar coordinates with k_θ angular slices and k_r radial steps. We then evaluate K at any (θ, r) using interpolation. This method accelerates computation since we do not need to use Equation 3 to repeatedly compute $K(\theta, r)$ from $K(0, r)$. The special case of $K(0, 0)$ results in a polar grid with a "bullseye" at the center (see Figure 3-Left).

We discretize angles finely and radii more coarsely. This choice is inspired by real-world observation that drivers tend to be more sensitive to the angle of an incoming car than its exact distance, Our equivariant kernels are computationally efficient and have very few parameters. Moreover, we will discuss later in Section 4.5 that despite discretization, the use of polar coordinates allows for very low equivariance error.

4.4 Hidden Layers as Regular Representations

The representation ρ_{reg} has shown better performance than ρ_1 for finite groups (Cohen et al., 2019a; Weiler & Cesa, 2019). But the naive ρ_{reg} representation $\{\varphi\colon G \to \mathbb{R}\}$ for an infinite group G is

too large to work with. We choose the space of square-integrable functions $L^2(G)$. It contains all irreducible representations of G and is compatible with pointwise non-linearities.

Discretization. However, $L^2(\mathrm{SO}(2))$ is still infinite-dimensional. We resolve this by discretizing the manifold S^1 underlying $\mathrm{SO}(2)$ into k_{reg} even intervals. We represent functions $f \in L^2(\mathrm{SO}(2))$ by the vector of values $[f(\mathrm{Rot}_{2\pi i/k_{\mathrm{reg}}})]_{0 \leq i < k_{\mathrm{reg}}}$. We then evaluate $f(\mathrm{Rot}_\theta)$ using interpolation.

We separate the number of angular slices k_θ and the size of the kernel k_{reg}. If we tie them together and set $k_\theta = k_{\mathrm{reg}}$, this is equivalent to implementing cyclic group $C_{k_{\mathrm{reg}}}$ symmetry with the regular representation. Then increasing k_θ would also increases k_{reg}, which incurs more parameters.

Convolution with Torus Kernel. In addition to constraining the kernel K of Equation 1 as in ρ_1, ρ_{reg} poses an additional challenge as it is a function on a circle. We introduce a new operator from functions on the circle to functions on the circle called a torus kernel.

First, we replace vectors in $\mathbb{R}^c$ with elements of $L^2(\mathrm{SO}(2))$. The input feature $\mathbf{f}$ becomes a ρ_{reg}-field, that is, for each $\mathbf{x} \in \mathbb{R}^2$, $\mathbf{f}^{(\mathbf{x})}$ is a function $S^1 \to \mathbb{R}$. For the kernel K, we replace the matrix field with a map $K\colon \mathbb{R}^2 \to \rho_{\mathrm{reg}} \otimes \rho_{\mathrm{reg}}$. Instead of a matrix, $K(\mathbf{x})$ is a map $S^1 \times S^1 \to \mathbb{R}$. Topologically, $S^1 \times S^1$ is a torus and hence we call $K(\mathbf{x})$ a *torus kernel.* The matrix multiplication $K(\mathbf{x}) \cdot f^{(\mathbf{x})}$ in Equation 1 must be replaced by the integral transform

$$K(\mathbf{x}) \circledcirc f^{(\mathbf{x})}(\phi_2) = \int_{\phi_1 \in S^1} K(\mathbf{x})(\phi_2, \phi_1) f^{(\mathbf{x})}(\phi_1) d\phi_1,$$

which is a linear transformation $L^2(\mathrm{SO}(2)) \to L^2(\mathrm{SO}(2))$. See the illustration in Figure 3-Right.

We compute Equation 2 for $\rho_{\mathrm{reg}} \to \rho_{\mathrm{reg}}$ as $K(\mathrm{Rot}_\theta(\mathbf{x}))(\phi_2, \phi_1) = K(\mathbf{x})(\phi_2 - \theta, \phi_1 - \theta)$. We can use the same weight sharing scheme as in Section 4.2.

4.5 Analysis: Equivariance Error

The practical value of equivariant neural networks has been demonstrated in a variety of domains. However, theoretical analysis (Kondor & Trivedi, 2018; Cohen et al., 2019a; Maron et al., 2020) of continuous Lie group symmetries is usually performed assuming continuous functions and using the integral representation of the convolution operator. In practice, discretization can lead the model to be not exactly equivariant but have some equivariance error $\mathrm{EE} = \|f(T(x)) - T'(f(x))\|$ (Wang et al., 2020, A6). Rectangular grids are well-suited to translations, but poorly-suited to rotations. The resulting equivariance error can be so large to practically undermine the advantages of a theoretically equivariant network.

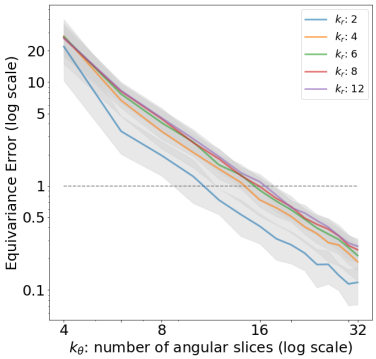

Figure 4: Experimentally, we find k_θ and expected equivariance error are inversely proportional.

The polar-coordinate indexed circular filters we propose are designed specifically to adapt well to the rotational symmetry we implement. In Figure 4 we demonstrate experimentally that expected EE is inversely proportional to k_θ. Choosing, e.g., $k_\theta \geq 16$ gives very low EE and does not increase the number of parameters. We also prove for ρ_1 features that the equivariance error has low expectation. See Appendix A.5 for the precise statement and proof.

Proposition. *Let $\alpha = 2\pi/k_\theta$, and $\bar{\theta}$ be θ rounded to nearest value in $\mathbb{Z}\alpha$, and $\hat{\theta} = |\theta - \bar{\theta}|$. Let $F = \texttt{CtsConv}_{K,R}$ and $T_\theta = \rho_1(\mathrm{Rot}_\theta)$. For some constant C, the expected* EE *is bounded*

$$\mathbb{E}_{K,\mathbf{f},\mathbf{x}}[T(F(\mathbf{f}, \mathbf{x})) - F(T(\mathbf{f}), T(\mathbf{x}))] \leq |\sin(\hat{\theta})| C \leq 2\pi C / k_\theta.$$

5 Experiments

In this section, we present experiments in two different domains, traffic and pedestrian trajectory prediction, where interactions among agents are frequent and the influence is obvious. We first

introduce the datasets and the metrics. Secondly, we compare different feature encoders and hidden feature representation types. Lastly, we compare our model with baselines.

5.1 EXPERIMENTAL SET UP

Dataset We discuss the performances of our models on (1) Argoverse autonomous vehicle motion forecasting (Chang et al., 2019), a recently released vehicle trajectory prediction benchmark, and (2) TrajNet++ pedestrian trajectory forecasting challenge (Kothari et al., 2020). For Argoverse, the task is to predict three-second trajectories based on all vehicles history in the past 2 seconds. We split 32K samples from the validation set as our test set.

Baselines We compare against several state-of-the-art baselines used in Argoverse and TrajNet++. We use three original baselines from (Chang et al., 2019): Constant velocity, Nearest Neighbour, and Long Short Term Memory (LSTM). We also compare with a non-equivariant continuous convolutional model, CtsConv (Ummenhofer et al., 2019) and a hierarchical GNN model VectorNet (Gao et al., 2020). Note that VectorNet only predicts a single agent at a time, which is not directly comparable with ours. We include VectorNet as a reference nevertheless.

Evaluation Metrics We use domain standard metrics to evaluate the trajectory prediction performance, including (1) Average Displacement Error (ADE): the average L2 displacement error for the whole 30 timestamps between prediction and ground truth, (2) Displacement Error at t seconds (DE@ts): the L2 displacement error at a given timestep t. DE@ts for the last timestamp is also called Final Displacement Error (FDE). For Argoverse, we report ADE and DE@ts for $t \in \{1, 2, 3\}$. For TrajNet++, we report ADE and FDE.

5.2 PREDICTION PERFORMANCE COMPARISON

We evaluate the performance of different models from multiple aspects: forecasting accuracy, parameter efficiency and the physical consistency of the predictions. The goal is to provide a comprehensive view of various characteristics of the model to guide practical deployment. See Appendix A.8 for an additional ablative study.

Forecasting Accuracy We compare the trajectory prediction accuracy across different models on Argoverse and TrajNet++. Table 2 displays the prediction ADE and FDE comparision. We can see that ECCO with the regular representation ρ_{reg} achieves on par or better forecasting accuracy on both datasets. Comparing ECCO and a non-equivariant counterpart of our model CtsConv, we observe a significant 14.8% improvement in forecasting accuracy. These results demonstrate the benefits of incorporating equivariance principles into deep learning models.

Model	Argoverse				TrajNet++		#Param
	ADE	DE@1s	DE@2s	DE@3s	ADE	FDE	
Constant Velocity	3.86	2.43	5.10	7.91	1.39	2.86	-
Nearest Neighbor	3.49	2.02	4.98	7.84	1.38	2.79	-
LSTM	2.13	1.16	2.81	4.83	1.11	2.03	50.6K
CtsConv	1.85	0.99	2.42	4.32	0.86	1.79	1078.1K
ρ_1-ECCO	1.70	0.93	2.22	3.89	0.88	1.83	51.4K
ρ_{reg}-ECCO	**1.62**	**0.89**	**2.12**	**3.68**	**0.84**	**1.76**	129.8K
VectorNet	1.66	0.92	2.06	3.67	-	-	72K + Decoder

Table 2: Parameter efficiency and accuracy comparison. Number of parameters for each model and their detailed forecasting accuracy at DE@ts.

Parameter Efficiency Another important feature in deploying deep learning models to embedded systems such as autonomous vehicles is parameter efficiency. The number of parameters has strong implications in memory usage, battery consumption and compute speed. We report the number of parameters in each of the models in Table 2. Compare with LSTM, our forecasting performance is better. CtsConv and VectorNet have competitive forecasting performance, but uses more parameters

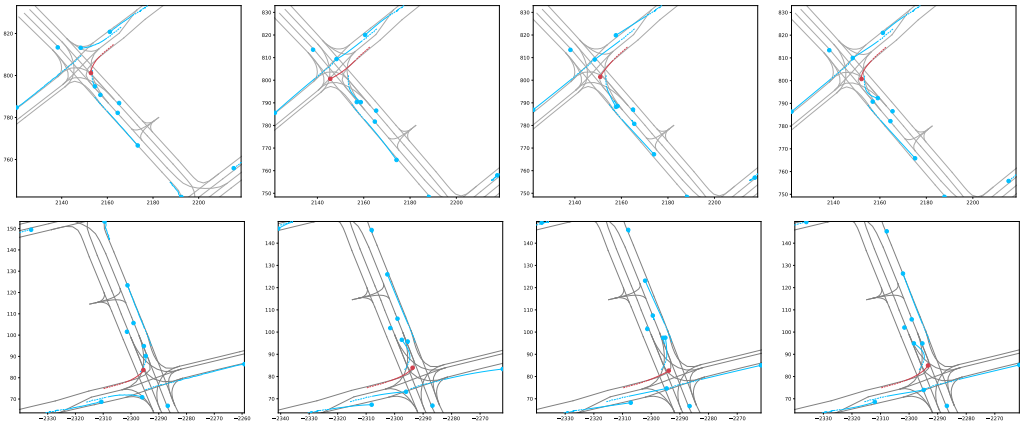

Figure 6: The x,y-axes are the position (m). The dashed line represents the 2s past trajectory. The solid line represents the 3s prediction. Red represents the agent. Top row: The predictions are made on the original data. Bottom row: We rotate the whole scene by 160° and make predictions on rotated data. From left to right are visualizations of ground truth, CtsConv, ρ_1-ECCO, ρ_{reg}-ECCO.

than ECCO. By encoding inductive bias of equivariance into CtsConv, we drastically reduce the number of the parameters needed in our model. For VectorNet, Gao et al. (2020) only provided the number of parameters for their encoder; a fair decoder size can be estimated based on MLP using 59 polygraphs with each 64 dimensions as input, predicting 30 timestamps, that is 113K.

Sample Efficiency For each sample an equivariant model is trained on, it learns as though it were trained on all transformations of that sample by the symmetry group (Wang et al., 2020, Prop 3). Thus ECCO requires fewer samples to train. In Figure 5, we plot a comparison of FDE over number of training samples and show the equivariant models converge faster.

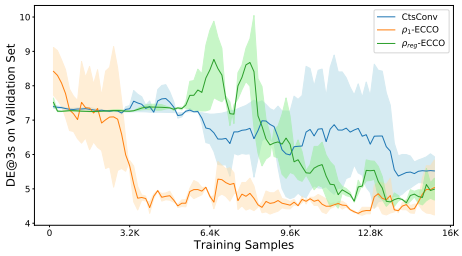

Figure 5: The training curves for equivariant models converge with fewer samples than the non-equivariant models.

Physical Consistency We also visualize the predictions from ECCO and non-equivariant CtsConv, as shown in Figure 6. Note that CtsConv predicts inconsistently: a right turn in the top row but a left turn after the scene has been rotated. We see similar results for TrajNet++ (see Figure 8 in Appendix A.9).

6 Conclusion

Many AI applications require more than low average error, they require consistent and physically realistic predictions. We work towards this goal for trajectory prediction. Our model ECCO achieves improved consistency by embedding the symmetries of the problem as inductive biases. On two real-world vehicle and pedestrians trajectory datasets, ECCO attains competitive accuracy with significantly fewer parameters. It is also more sample efficient; generalizing automatically from few data points in any orientation. Lastly, equivariance gives ECCO improved generalization performance. Our method provides a fresh perspective towards increasing trust and transparency in deep learning models. Future directions include applying equivariance to problem of predicting a distribution of many possible trajectories.

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