GEOPT: SCALING PHYSICS SIMULATION VIA LIFTED GEOMETRIC PRE-TRAINING

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ABSTRACT

Neural simulators promise efficient surrogates for physics simulation, but scaling them is bottlenecked by the prohibitive cost of generating high-fidelity training data. Pre-training on abundant off-the-shelf geometries offers a natural alternative, yet faces a fundamental gap: supervision on static geometry alone ignores dynamics and can lead to negative transfer on physics tasks. We present **GeoPT**, a unified pre-trained model for general physics simulation based on *lifted geometric pre-training*. The core idea is to augment geometry with synthetic dynamics, enabling dynamics-aware self-supervision without physics labels. Pre-trained on over one million samples, GeoPT consistently improves industrial-fidelity benchmarks spanning fluid mechanics for cars, aircraft, and ships, and solid mechanics in crash simulation, reducing labeled data requirements by 20-60% and accelerating convergence by $2\times$. These results show that lifting with synthetic dynamics bridges the geometry-physics gap, unlocking a scalable path for neural simulation and potentially beyond. Code is available at https://github.com/Physics-Scaling/GeoPT.

1 INTRODUCTION

Neural simulators have emerged as efficient surrogates for classical numerical solvers, accelerating physics simulation across scientific discovery and engineering design (Li et al., 2021; Wang et al., 2023; Zhou et al., 2024). By learning an operator that maps geometry and initial conditions to solution fields, these models reduce complex evaluations to a single forward pass, substantially lowering inference costs. This amortization is particularly vital for iterative design systems, as evidenced by the widespread adoption of commercial neural simulation software within industrial design (Ansys Inc., 2026; Altair Engineering Inc., 2026a).

Achieving industrial-fidelity accuracy, however, typically hinges on scaling model capacity and training data. Unlike vision or language, where well-established self-supervision learning methods and web-scale data enable such scaling (He et al., 2022; Achiam et al., 2023), neural simulators remain dominated by *supervised learning* on physics data generated from numerical solvers. The primary scaling bottleneck is label generation: each training sample requires a full numerical solve, whose computational cost increases sharply with geometry and physics complexity. For example, in the DrivAerML aerodynamics dataset (Ashton et al., 2024), generating a single industrial-fidelity sample can cost 6.1×10^4 CPU-hours. This prohibitive cost severely limits the scaling of neural simulators across diverse physics.

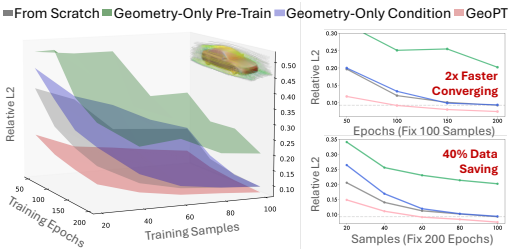

Figure 1: Neural aerodynamics simulation on DrivAerML (Ashton et al., 2024) based on Transolver (Wu et al., 2024) backbone. Geometry-only pre-training and conditioning refer to pre-training by predicting vector distance (Faugeras & Gomes, 2000) of given positions and utilizing geometry representation extracted by Hunyuan3D (Tencent, 2025) as auxiliary feature, respectively.

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Figure 2: GeoPT offers a way to scale up neural simulators with off-the-shelf geometries for physics.

In this paper, we explore *self-supervised pre-training* for neural simulation as a pathway to scale beyond solver-simulated datasets. Fundamentally, the solution field of a physical system is jointly determined by geometry and dynamics: the geometry defines the spatial domain and boundaries, while dynamics specify how the system is driven. Although physics labels from geometry-dynamics coupled simulations are costly to obtain, the geometry alone is abundantly available at web scale from public repositories (Chang et al., 2015; Deitke et al., 2023). This asymmetry motivates a *geometric pre-training* paradigm: we pre-train neural simulators only on geometry data and introduce simulated physics labels during downstream fine-tuning.

The central challenge is that previous self-supervised learning methods only optimize the model within the *native space* of the pre-training data, such as learning to reconstruct from masked images (He et al., 2022) or learning to identify similar samples from augmentations (Chen et al., 2020), where the model input will not exceed the original information of pre-training data. This paradigm succeeds when the pre-training data space is aligned with downstream tasks, such as image pre-training for recognition. However, a fundamental gap emerges when the downstream task inhabits a space strictly richer than that of the pre-training data. Neural simulation exemplifies this failure: while pre-training on geometry data is viable, the downstream task requires representations that encode the coupled interaction of geometry and dynamics, while geometry-only pre-training can only learn a reduced representation. As evidenced empirically in Fig. 1, geometry-only supervision for pre-training cannot benefit or even degrade downstream performance.

To bridge this gap, we propose *dynamics-lifted geometric pre-training*, defining supervision within an expanded space that reflects the geometry-dynamics coupling required by downstream tasks. Specifically, we augment the geometry-only pre-training input with randomly sampled velocity fields as dynamics conditions and leverage the dynamics-induced, geometry-bounded transport trajectories as self-supervision. Such pre-training can go beyond the original geometry space and enables the model to learn geometry-dynamics coupled representations in a lifted space. After pre-training, the model is fine-tuned to specific physics tasks by specializing the dynamics condition with the corresponding simulation settings and learning from solver-generated labels. In effect, this *lifted self-supervision* learns a dynamics-aware prior from massive unlabeled geometry, scaling without task-specific simulation during pre-training.

We perform dynamics-lifted geometric pre-training on a large-scale 3D geometry repository, generating over one million solver-free geometric-walk samples by sampling dynamics conditions for each shape. We refer to the resulting geometric pre-trained model as **GeoPT**. GeoPT consistently improves downstream accuracy and data-efficiency across industrial-fidelity fluid and solid benchmarks, including car, aircraft aerodynamics, ship hydrodynamics and crash simulation (Figs. 1-2), which reduces physics data requirements by 20-60%, accelerates convergence by up to $2\times$ and can generalize to boarder physics domains, e.g., radiosity, unlocking the scaling benefits of neural simulators.

2 Related Work

2.1 Neural Simulators

Our review focuses on the evolution of neural simulators, which we categorize into model architectures and foundation models. For classical solvers, we refer readers to established reviews (Ŝolín, 2005).

Model architectures. Extensive architectures have been explored for neural simulation (Raissi et al., 2020; Pfaff et al., 2021), with neural operators representing notable progress by formalizing simulation as learning maps between function spaces (Kovachki et al., 2023) to solve PDEs. FNO (Li et al., 2021) and its variants (Wen et al., 2022; Li et al., 2023b; Rahman et al., 2023; Wu et al., 2023) approximate integral operator via linear transformations in Fourier space. Transformers (Vaswani et al., 2017) have

also been adopted (Li et al., 2023a; Wu et al., 2024), where the attention mechanism serves as a global integral operator (Kovachki et al., 2023), and naturally accommodates irregular geometries by treating mesh points as tokens. To address the quadratic complexity in geometric resolution, efficient attention (Choromanski et al., 2021) and its variants are introduced to Transformer-based simulators (Cao, 2021; Hao et al., 2023). Recently, Transolver (Wu et al., 2024) bypasses mesh structure by learning latent physical states, demonstrating strong performance and scaling in industrial design applications (Luo et al., 2025; Nabian et al., 2025). In this paper, we use Transolver as our backbone, although the proposed pre-training method is architecture-agnostic.

Physics foundation models. Scaling neural simulators as physics foundation models has been explored to improve simulation performance (Yang et al., 2023; Herde et al., 2024; Ye et al., 2024). Poseidon pre-trains on 2D fluid dynamics with temporal conditioning (Herde et al., 2024); DPOT expands to diverse physics with auto-regressive prediction (Hao et al., 2024); Unisolver incorporates PDE information via conditional architectures (Zhou et al., 2025); and P3D extends to 3D fluids (Holzschuh et al., 2025). Despite these advances, existing models remain restricted to a specific physics family on regular grids and do not generalize to the industrial simulations evaluated in this paper. Moreover, they still rely on compute-heavy simulation data for scaling, whereas GeoPT pre-trains on off-the-shelf geometries alone, offering a more scalable path to large-scale pre-training.

2.2 Self-Supervised Pre-Training

Self-supervised pre-training has achieved remarkable success in vision (Caron et al., 2021; He et al., 2022; Lin et al., 2023), language (Achiam et al., 2023), and audio (Huang et al., 2022), typically by constructing pretext tasks to learn transferable representations that mitigate labeling bottlenecks.

Well-established methods include reconstructing masked inputs (Vincent et al., 2008; He et al., 2022; Xie et al., 2022) and predicting similarity among augmentations (He et al., 2020; Chen et al., 2020; Caron et al., 2021). Despite the diverse pretext tasks, these methods limit the learning process within the pre-training data space without introducing external information. This paradigm is widely adopted for input-aligned pre-training and fine-tuning tasks. Our setting differs fundamentally: we pre-train on geometry yet target generalization to the higher-dimensional physics space, where native-space pre-training may collapse due to potential randomness of uncovered factor, e.g., dynamics.

Self-supervised pre-training has also been explored in 3D geometry (Yu et al., 2022; Tencent, 2025), and recent work incorporates such pre-trained encoders as auxiliary feature extractors for physics-learning (Zhang et al., 2025). However, these approaches rely on frozen geometric encoders and do not scale the core physics backbone. Furthermore, since pre-training uses static geometric supervision only, the learned representations lack awareness of dynamics. In contrast, we directly pre-train the physics backbone itself and bridge the geometry-physics gap through dynamics-lifted pre-training.

3 Problem Setup

We consider physics systems defined with geometric objects $G \in \mathcal{G}$, where $\mathcal{G}$ denotes the space of geometries in $\mathbb{R}^C$, and system conditions $S \in \mathcal{S}$ that specify how the system is driven, including boundary types, external forces, governing equation, initial states, etc. The numerical simulator produces a solution $\boldsymbol{u}: \mathbb{R}^C \to \mathbb{R}^{C_{\mathbf{u}}}$, where $\boldsymbol{u}(\mathbf{x})$ is the corresponding physics quantities on discretized mesh points $\mathbf{x} \in \mathbb{R}^C$ and $C_{\mathbf{u}}$ denotes the number of physical variables. In this work, we focus on steady-state simulation, a primary paradigm for industrial design and large-scale engineering analysis. For example, in aerodynamics, G is a car surface mesh, S specifies incoming flow velocity and direction, $\mathbf{x}$ denotes the query point, and $\boldsymbol{u}(\mathbf{x})$ contains the resulting pressure and velocity fields.

The neural simulator $\mathcal{F}_\theta(G, S)$ learns to estimate the physical quantities directly, bypassing the expensive numerical solvers. The learning objective is to minimize:

$$\mathcal{L}^{\text{physics}} = \mathbb{E}_{\mathcal{D}} \left[\| \mathcal{F}_\theta(\mathbf{x}; G, S) - \boldsymbol{u}(\mathbf{x}) \|_2^2 \right]. \tag{1}$$

Previous supervised learning relies on labeled dataset $\mathcal{D} = \{(\mathbf{x}, G, S, \boldsymbol{u}(\mathbf{x}))\}$. The geometric pre-training studied in this paper seeks an initialization $\widehat{\theta}$ for $\mathcal{F}_\theta$ from unlabeled geometries $\mathcal{G}$ alone, so that the downstream optimization of Eq. 1 converges faster with fewer physics labels.

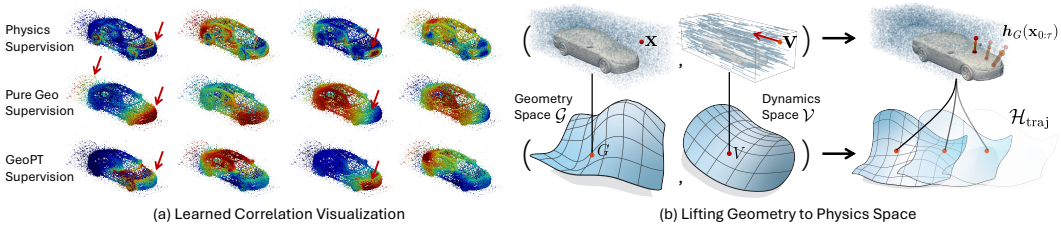


Figure 3: Geometry-physics analysis. (a) Visualization of learned correlations on DrivAerML (Ashton et al., 2024). We train Transolver (Wu et al., 2024) using different supervisions and visualize the spatial distribution of learned aggregation weights in four tokens. Brighter colors indicate higher token assignment likelihood, revealing correlations captured by the model. (b) We lift the geometry space by augmenting it with synthetic velocity fields, which further derive a dynamics-aware supervision.

4 METHOD

We aim to pre-train a general neural simulator solely from geometric data. This requires a supervision signal that reflects the geometry-dynamics coupling of downstream tasks, while enabling adaptation to diverse simulations. GeoPT achieves this through lifted geometric pre-training, which naturally yields a unified interface for varied physics tasks.

4.1 LIFTING GEOMETRY TO PHYSICS

The geometry-physics gap. Given the abundance of unlabeled 3D shapes, a natural strategy is to pre-train neural simulators using supervision derived purely from geometry. A straightforward approach trains the model to predict geometric features at query points $\mathbf{x}$ with following loss:

$$\mathcal{L}_{\text{native}}^{\text{pre}} = \mathbb{E}_{\mathbf{x},G}\left[\|\mathcal{F}_{\widehat{\theta}}(\mathbf{x};G) - \boldsymbol{h}_G(\mathbf{x})\|_2^2\right], \tag{2}$$

where $\boldsymbol{h}_G(\mathbf{x}) \in \mathcal{H}$ denotes the self-supervision target at $\mathbf{x}$, with $\mathcal{H}$ being the space of geometric features such as occupancy, signed distance (SDF), or vector distance fields (Faugeras & Gomes, 2000). We refer to this as *native pre-training*: the model learns a mapping $\mathcal{G} \to \mathcal{H}$, where the supervision $\boldsymbol{h}_G(\mathbf{x})$ is derived solely from the geometry, determined by static spatial information G.

Despite the intuition that pre-training should help, the objective in Eq. 2 does not reliably benefit neural simulation in practice. We empirically study this on the aerodynamics task in DrivAerML (Ashton et al., 2024) using Transolver (Wu et al., 2024). Quantitatively, as shown in Fig. 1, native pre-training followed by fine-tuning on physics labels degrades accuracy compared to training from scratch by a large margin. To understand this failure, we visualize the learned aggregation weights across spatial points in Transolver[1], which represent the spatial correlations the model has learned and can reflect the potential interactions among different positions under the physical simulation context. We compare: (i) training with physics supervision, and (ii) training with geometry-only supervision from Eq. 2. As shown in Fig. 3(a), the two settings yield starkly different patterns. With geometry-only supervision, the model groups regions by static shape cues, assigning both front and back volumes to the same state and producing left-right asymmetric patterns. In contrast, physics supervision yields front-back asymmetric and left-right symmetric patterns that align with the aerodynamic flow.

The root cause of this failure becomes clear when comparing native pre-training (Eq. 2) with the downstream task (Eq. 1). Downstream prediction depends jointly on geometry G and dynamics conditions S, yet native pre-training involves only G, where dynamics are entirely absent. Without any notion of dynamics, native pre-training cannot capture the geometry-dynamics coupled physics.

Parameterize dynamics. To bridge this gap, we need to design a pre-training objective that incorporates dynamics while relying only on geometry data: the supervision should remain geometry-derived, yet the learning process should also encode dynamics. A key question is how to represent dynamics S in a form amenable to self-supervised learning.

[1]Transolver aggregates mesh points into several internally representation-consistent tokens. If two positions are more likely to be ascribed to the same token, they are learned to be correlated.

We begin by examining how particles behave in physical systems. In any dynamic process, a particle at position $\mathbf{x}$ is not static but moves under the governing physics. This evolution can be characterized by an (instantaneous) velocity field $\boldsymbol{v}_S : \mathbb{R}^C \times \mathbb{R} \to \mathbb{R}^C$ determined by the simulation settings S, which can be formalized as:

$$\frac{\mathrm{d}\mathbf{x}_t}{\mathrm{d}t} = \boldsymbol{v}_S(\mathbf{x}_t, t) \cdot \mathbb{1}_G(\mathbf{x}_t), \quad \mathbf{x}_0 = \mathbf{x}, \tag{3}$$

where $\mathbb{1}_G(\cdot)$ equals 0 inside or on the boundary G and 1 otherwise. This formulation encodes two key structures of physical simulation: (i) The velocity field $\boldsymbol{v}_S$ couples spatially distant points: trajectories from different initial positions may intersect, causing these points to share correlated physical responses, mirroring how quantities at different locations become coupled through shared flow or force transmission. (ii) The indicator $\mathbb{1}_G$ halts trajectories at the geometry boundary, reflecting that physical responses are fundamentally shaped by boundary interactions, e.g., surface pressure in aerodynamics, contact forces in crash simulation, or radiosity in light transport. This formulation is generic across physical regimes: in fluid dynamics, $\boldsymbol{v}_S$ relates to the flow velocity; in solid mechanics, it describes the displacement; in radiative transport, it represents propagation direction. The velocity field $\boldsymbol{v}_S$ thus provides a fundamental parameterization of dynamics conditions S.

Lifting geometry via synthetic dynamics. This observation offers a path to incorporating dynamics into pre-training. Rather than relying on the physics-determined $\boldsymbol{v}_S$, which requires expensive simulation to obtain, we construct *synthetic velocities* by randomly sampling per-particle velocity:

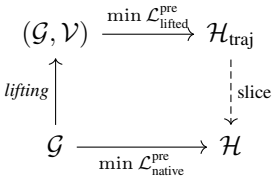
$$\frac{\mathrm{d}\mathbf{x}_t}{\mathrm{d}t} = \mathbf{v} \cdot \mathbb{1}_G(\mathbf{x}_t), \quad \mathbf{x}_0 = \mathbf{x}, \quad \mathbf{v} \sim \mathrm{Unif}(\mathbb{B}^C), \tag{4}$$

where $\mathbb{B}^C = \{\mathbf{v} \in \mathbb{R}^C : \|\mathbf{v}\|_2 \leq v_{\max}\}$. Denote $V \in \mathcal{V}$ as the collection of such per-point velocities across all query points as shown in Fig. 3(b).

The self-supervision target then becomes geometric feature trajectory under synthetic dynamics:

$$\boldsymbol{h}_G(\mathbf{x}_{0:\tau}) = \{\boldsymbol{h}_G(\mathbf{x}_t)\}_{t=0}^{\tau} \in \mathcal{H}_{\text{traj}}, \tag{5}$$

where τ is a given fixed time horizon. By tracking how geometric features evolve along these synthetic trajectories, we obtain a *dynamics-aware* supervision signal constructed entirely from geometry.



In effect, we *lift* the pre-training from the native geometry space to a joint geometry-dynamics space. The inset diagram illustrates the key relationships: the vertical arrow $\mathcal{G} \to (\mathcal{G}, \mathcal{V})$ is the *lifting* operation, augmenting each geometry with random velocity fields; the top arrow $(\mathcal{G}, \mathcal{V}) \to \mathcal{H}_{\text{traj}}$ is the *lifted pre-training* task, predicting feature trajectories under synthetic dynamics; the bottom arrow $\mathcal{G} \to \mathcal{H}$ is *native pre-training*; and the dashed arrow $\mathcal{H}_{\text{traj}} \to \mathcal{H}$ is *slicing*, which recovers static features by taking $t = 0$. Native pre-training is thus a degenerate case of lifted pre-training: when dynamics are removed, the trajectory collapses to a single point. Crucially, downstream simulation also operates on the joint space $(\mathcal{G}, \mathcal{V})$, representations learned via lifting therefore transfer directly to physics simulation tasks.

Remark 4.1 (**Theoretical interpretation**). The trajectory evolution in Eq. 4 corresponds to solving a fundamental mass-conservation system, described by the transport equation with sticking boundary: $\partial_t f + v \cdot \nabla_x f = 0$, where $f(x, v, t)$ is a phase-space density. Pre-training with randomly sampled velocity fields $v \in \mathcal{V}$ can be viewed as learning to obey the conservation law under arbitrary dynamics, providing a universal prior for the downstream physical simulation. See Appendix A for details.

4.2 Lifted Geometric Pre-Training

The above-described dynamics-lifted framework provides both a pre-training objective and a unified interface for downstream tasks: the model receives geometry and velocity as input during both pre-training and fine-tuning. We now present the complete GeoPT system.

Pre-training objective. Following the lifting perspective, we pre-train the model to predict geometric feature trajectories under synthetic dynamics:

$$\boxed{\mathcal{L}^{\text{pre}}_{\text{lifted}} = \mathbb{E}_{\mathbf{x}, G, V}\left[\left\|\mathcal{F}_{\widehat{\theta}}(\mathbf{x}; G, V) - \boldsymbol{h}_G(\mathbf{x}_{0:\tau})\right\|_2^2\right].} \tag{6}$$

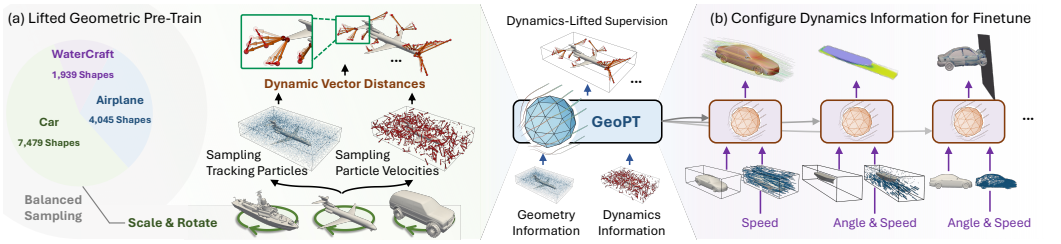


Figure 4: GeoPT. (a) To ensure the pre-training diversity, we pre-train the model with geometry randomly sampled from the public repository (Chang et al., 2015) and generate the supervision for random tracking points under random dynamics. (b) Through a dynamics-lifted framework, we can configure the dynamics condition to "prompt" the corresponding pre-training capability of GeoPT.

The expectation is over three sources of variation (Fig. 4): (i) geometry G sampled with category-balanced sampling from the geometry dataset $\mathcal{G}$, (ii) tracking point initial position $\mathbf{x}$ sampled from both the surrounding volume space Ω_G and geometry boundary G, and (iii) per-point velocity $\mathbf{v} \in V$ sampled uniformly from a bounded ball $\mathbb{B}^C$. Given geometry-dynamics coupled information (G, V), the trajectory $\mathbf{x}_{0:\tau}$ is deterministically computed via Eq. 4, and the supervision target $\boldsymbol{h}_G(\mathbf{x}_{0:\tau}) = \{\boldsymbol{h}_G(\mathbf{x}_t)\}_{t=0}^{\tau}$ is the sequence of geometric features along this path.

The composition of these three factors yields a *combinatorially* large pre-training space: each geometry admits infinitely many query positions, and each position can be paired with arbitrary velocities, enabling massive data generation from a finite set of shapes. The model $\mathcal{F}_{\widehat{\theta}}$ receives query position $\mathbf{x}$, velocity V, and geometry G, and outputs a feature trajectory instead of static geometry features. Thus, the whole learning process lies in a higher-dimensional space than native input.

As shown in Fig. 4, we pre-train on industry-relevant subsets of ShapeNet (Chang et al., 2015) (cars, airplanes, watercraft), comprising over 10,000 unique geometries. Although these shapes differ from industrial models, they provide foundational knowledge of real-world geometries. Coupled with multiple dynamic trajectories per geometry, our pre-training leverages 1,346,300 samples in total.

Fast Fine-tuning. After pre-training, GeoPT captures physics-aligned correlations conditioned on the velocity. As shown in Fig. 4(b), GeoPT adapts to downstream simulation tasks by replacing randomly sampled velocities with task-specific velocity $V_S = \{\mathbf{v}_S\}$ that encode the simulation settings S from Eq. 1. The fine-tuning objective is:

$$\mathcal{L}^{\text{fine}} = \mathbb{E}_{\mathbf{x},G,V_S}\left[\|\mathcal{F}_\theta(\mathbf{x}; G, V_S) - \boldsymbol{u}(\mathbf{x})\|_2^2\right]. \tag{7}$$

The key is configuring V_S to explicitly encode simulation settings S. Here are examples for Table 1:

(i) Aerodynamics: S specifies incoming flow conditions, including angle of attack, sideslip angle, and freestream velocity. We encode these as V_S with direction aligned to the flow and magnitude equal to the freestream speed. This covers both car and airplane simulations.

Table 1: Summary of experimental simulations. #Mesh records the size of the discretized meshes for each sample. #Variable records the varied simulation configurations among different samples. #Size record the disk usage for the dataset.

Type	Benchmarks	#Mesh	#Variable	#Size
Aero-dynamics	DrivAerML	∼160M	Geometry	∼6TB
	NASA-CRM	∼450k	Geo, Speed, AoA	∼3GB
	AirCraft	∼330k	Geo, Speed, AoA, Slip	∼7GB
Hydro-	DTC Hull	∼240k	Geo, Yaw Angle	∼2GB
Crash	Car-Crash	∼1M	Impact Angle	∼8GB

(ii) Hydrodynamics: S specifies vessel speed and water-air interface conditions. We configure separate V_S for water and air phases, with directions and magnitudes reflecting the two-phase flow in ship resistance simulation.

(iii) Crash simulation: S specifies impact location, direction, and material properties. We encode these as V_S with direction aligned to the impact and spatially decaying magnitude from the collision point, reflecting force propagation.

This unified interface, geometry G plus velocity field V_S, allows a single pre-trained model to adapt to diverse physics by reconfiguring the velocity input.

Remark 4.2 (**Native space v.s. lifted pre-training**). By comparing native space (Eq. 2) and lifted (Eq. 6) pre-training formalizations, we can establish the theoretical connection between these two paradigms. Given optimal models $\mathcal{F}_{\theta^*_{\text{native}}}$ and $\mathcal{F}_{\theta^*_{\text{lifted}}}$ achieving zero $\mathcal{L}^{\text{pre}}_{\text{native}}, \mathcal{L}^{\text{pre}}_{\text{lifted}}$ respectively, we have

$$\text{slice}\left(\mathbb{E}_V\left[\mathcal{F}_{\theta^*_{\text{lifted}}}(\mathbf{x}; G, V)\right]\right) = \mathcal{F}_{\theta^*_{\text{native}}}(\mathbf{x}; G), \tag{8}$$

where slice denotes taking $t = 0$. This can be easily proven based on the definition of $\boldsymbol{h}_G$ in Eq. 5. This equation indicates that the canonical native-space pretraining essentially learns the expectation of our lifted paradigm, which may lead to information loss and degenerated representations. In contrast, lifted pre-training learns the spanned manifold, where the dynamics V can also serve as the "key" to retrieve corresponding capability learned during pre-training.

4.3 Implementation Details

We provide key implementation details here; full configurations can be found in Appendix E.

Backbone. We adopt Transolver (Wu et al., 2024), a recent geometry-general neural solver, as our default backbone. We configure three model sizes for scaling experiments: base (8 layers, 3M parameters), large (16 layers, 7M parameters), and huge (32 layers, 15M parameters), all with 256 hidden channels and 32 state tokens. Note that neural simulators typically operate at smaller scales than vision or language models; 15M parameters represents a substantial model for this domain.

Pre-training data. We discretize the trajectory in Eq. 4 into 3 steps for a balance between expressiveness and efficiency. For geometric features $\boldsymbol{h}_G(\cdot)$, we use vector distance (Faugeras & Gomes, 2000) to encode global geometry information. All geometries are normalized to unit scale with consistent orientation. For each geometry, we sample 32,768 volume points and 4,096 surface points, with per-point velocities sampled from a bounding ball with radius as 2. For diversity, we generate 100 random dynamics fields per geometry, yielding a million-scale pre-training dataset.

Computational cost. The supervision signal in Eq. 6 can be computed efficiently via optimized ray-triangle intersection (Sawhney, 2021). Tracking 36,864 points within one geometry-dynamics sample takes approximately 0.2 seconds on 80 CPU cores, roughly $10^7\times$ faster than industrial-scale CFD simulation (2024). We pre-compute all supervision data offline, resulting in a $\sim$5TB dataset, which only takes around 3 days with 80 CPU cores, showing the scalability of geometric pre-training.

Training settings. As described above, we sample the same number of tracking particles for all kinds of geometry. Therefore, the pre-training processes are naturally aligned, where the input includes geometry information (i.e., position, SDF and normal), sampled dynamics information (i.e., direction vector and magnitude) of all tracking particles, and the output is 3-step vector distance. As for the fine-tuning, the input dimension remains the same, which contains geometry information and configured dynamics. To adapt to various simulation tasks, we adjust the output dimension of the final projection layer to the number of required physics quantities and conduct full parameter fine-tuning.

5 Experiments

We extensively evaluate GeoPT in five industrial-scale physics simulation tasks, which involve complex geometries and diverse simulation configurations.

Benchmarks. As summarized in Table 1, we examine the model performance on extensive 3D industrial-scale simulations. For aerodynamics, we test Reynolds-Averaged Navier-Stokes (RANS) simulation with DriAverML (Ashton et al., 2024), NASA-CRM (Bekemeyer et al., 2025) and AirCraft (Luo et al., 2025), which are representative high-fidelity data for 3D car and aircraft simulations and require predicting the surface pressure and surrounding wind. As for the hydrodynamics simulation DTCHull, we generate different geometries with ship parameterization (Bagazinski & Ahmed, 2023) and then simulate the ship resistance and wave-making under different geometries and yaw angles with RANS using OpenFOAM (Jasak, 2009), where the model is trained to predict the time-averaged surface pressure and water flow speed. The Car-Crash benchmark is based on an industrial standard model and simulated under different impact angles with OpenRadioss (Altair Engineering Inc., 2026b), where the maximum 2D Von Mises stress for each element during crash is recorded. Although the base geometry is fixed, it involves deformations during crash.

To mimic the industrial practice (Ansys Inc., 2026), we adopt or generate $\sim$100 training samples for each benchmark and test neural simulators on the other 20–50 samples.

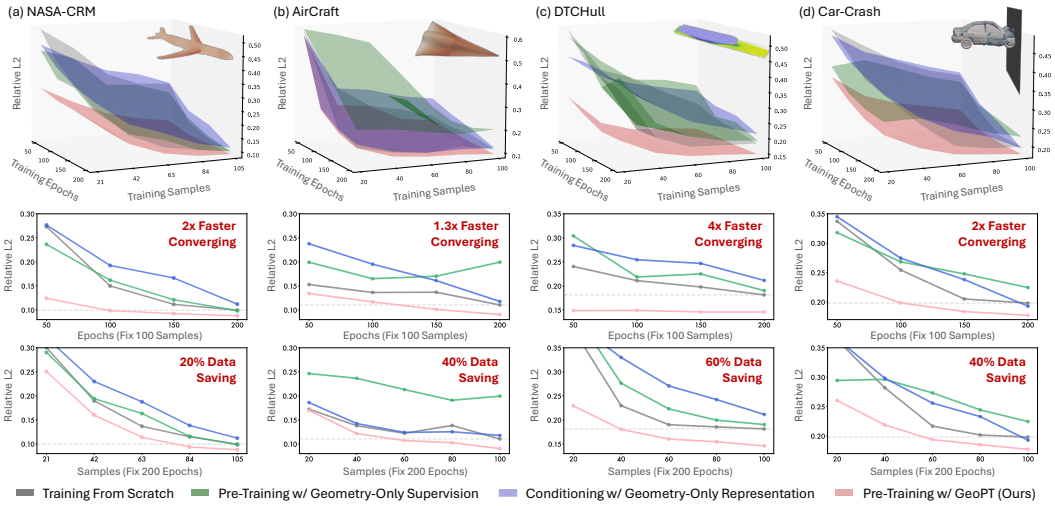


Figure 5: Performance across fine-tuning epochs and physics samples. We show detailed curves at 200 epochs and 100 samples for clarity. Here, geometry-only pre-training adopts vector distance.

Baselines. GeoPT mainly focuses on the self-supervised pre-training of neural simulators, which has not been well studied previously. Therefore, we adopt native geometry space pre-training: given position information to predict SDF and vector distance, as baselines. Experimentally, since SDF-based pre-training is much worse than vector distance, we defer the SDF-related experiments to Appendix B. Besides, we also compare with the geometry-conditioned paradigm, where we adopt the VAE encoder from the advanced 3D geometry model Hunyuan3D (2025) to extract geometry representations as an auxiliary feature. Additionally, GeoPT is built upon the advanced geometry-general backbone Transolver (2024). Other Transformer simulator backbones, including Galerkin Transformer (2021), GNOT (2023), UPT (2024) and Transolver++ (2025), are also compared. All methods are under the same training strategy to ensure a fair comparison.

5.1 Main Results

Accelerating simulation. As a supplement to Fig. 1, we further benchmark GeoPT on the other four simulation tasks in Fig. 5, where we can observe that:

(i) Reducing simulation data requirements. GeoPT consistently improves a wide range of physics simulations, reducing 20–60% data requirements while reaching performance comparable to full-data training. This improvement is particularly significant in industrial settings, where generating a single training sample may require hours or even days of numerical simulation (Ashton et al., 2024; Bekemeyer et al., 2025). By substantially reducing the amount of simulation data required, GeoPT can alleviate the data bottleneck in AI-enabled industrial workflows (Ansys Inc., 2026).

(ii) Improving geometry generalization. GeoPT yields larger improvements in simulations involving a greater diversity of geometries. For instance, GeoPT brings 60% data requirement reduction on DTCHull, where samples exhibit substantial geometric variability in hull curvatures and length-to-beam ratios. In such cases, pre-training on diverse geometries enables GeoPT to better generalize across heterogeneous geometric configurations. In contrast, GeoPT yields a moderate improvement on NASA-CRM, as the geometric variations among samples are primarily limited to changes in inboard and outboard aileron angles, which only induce slight local deformations in the wing region.

(iii) Supporting surface-only simulation. Although our pre-training involves both volume and surface points, GeoPT is also applicable to purely surface-related simulations, such as Car-Crash. By configuring a decayed velocity field on the car surface as the dynamics condition, GeoPT can adapt to this scenario. This flexibility arises from the stochastic nature when generating dynamics-lifted supervision, which encourages the model to capture a broader range of geometry–physics correlations.

Scalability. As a self-supervised model, GeoPT demonstrates favorable scalability in both model and data aspects, showing a promising potential to serve as a physics foundation model.

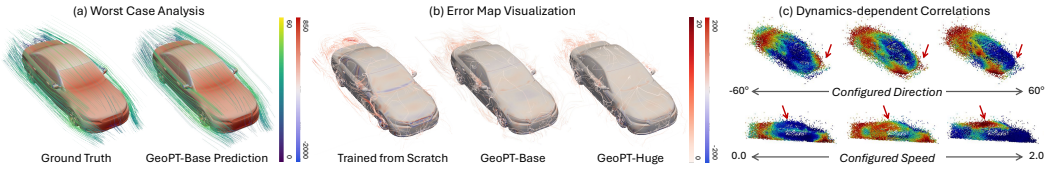


Figure 7: (a) Visualization of the prediction results with the worst relative L2 performance in DrivAerML; (b) The error map of surface pressure and surrounding velocity; (c) Correlations learned by pre-trained GeoPT under varied dynamics, such as different directions and speeds of V_S. More showcase studies and representation visualizations can be found in Appendix D and F.

(i) Model size. As presented in Fig. 6(a), although the backbone Transolver (2024) shows nice scalability in sufficient data scenarios, as reported in their paper, it still faces a scaling bottleneck in limited-data industrial simulation, which may be caused by overfitting. In contrast, pre-training with large-scale geometry data can regularize the model hypothesis space to alleviate potential overfitting, thereby consistently benefiting from increasing model size.

This model scaling curve also verifies the value of our generated pretraining data, which provides sufficient data diversity and prior knowledge to be learned.

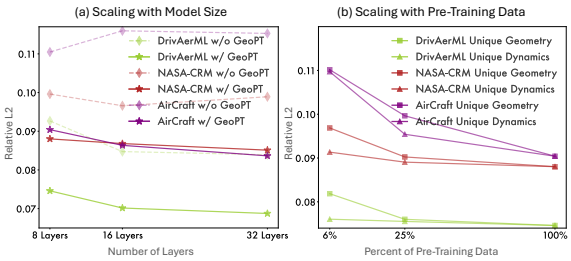


Figure 6: GeoPT scaling tests. (a) Gradually increase model layers from 8 to 32 and record the performance change of training from scratch and with GeoPT. (b) Reduce the pre-training diversity of both geometries and dynamics. See Appendix F for full results.

(ii) Data diversity. In GeoPT, we construct a million-scale pre-training dataset by simulating 100 dynamic trajectories for each unique geometry. To investigate the effect of the pre-training diversity, we separately reduce the number of unique geometries and sampled dynamic trajectories. Results in Fig. 6(b) demonstrate that, compared to dynamic trajectories, the diversity of base geometries is more important to downstream performance. Additionally, the benefit of pre-training dynamics diversity is also task-specific. For example, in DrivAerML with fixed incoming flow, sampling 6% dynamic trajectories can already be comparable to 100 samples, while in AirCraft with varied speed, AoA and sideslip, sampling more dynamic trajectories can significantly increase fine-tune performance, highlighting the potential of GeoPT in handling more complex simulations.

Worst case visualization. We plot the worst prediction case of GeoPT in Fig. 7, where GeoPT still accurately estimates the complex aerodynamics surrounding the car. As demonstrated in Fig. 7(b), compared to training from scratch, GeoPT can improve the prediction accuracy of wake flow and can be further improved by parameter scaling. Besides, empowered by large-scale pre-training, GeoPT can capture diverse underlying correlations under a proper dynamics prompt. As shown in Fig. 7(c), conditioned on different velocity V_S, GeoPT can capture different correlation patterns, such as the inclined correlation under crosswind and the more concentrated correlation under high speed. Especially, under zero speed, our supervision degenerates to static geometry.

5.2 Model Analysis

Geometry usage. We provide a detailed ablation of how geometric information is utilized in Fig. 8(a).

(i) Geometry-only v.s. dynamics-lifted. Previously, we have extensively discussed the advantage of dynamics-lifting in pre-training. Here, we further explore the representation conditioning usage of GeoPT. For comparison, we adopt geometry representations from the large-scale pre-trained Hunyuan3D (2025) as the baseline, which employs SDF-based geometry reconstruction. While Hunyuan3D representations are effective for accurate geometry reconstruction, they remain insufficient in helping physics simulation (green curve). In contrast, GeoPT employs dynamics-lifted supervision, enabling the model to learn physics-aligned representations (red curve). Thus, GeoPT helps under both pre-training and conditioning, highlighting the essentiality of dynamics lifting.

(ii) Pre-training v.s. conditioning. Unlike prior works that incorporate geometry information as frozen auxiliary features, GeoPT directly leverages geometry to pre-train the physics-learning backbone. Fig. 8(a) shows that pre-training the backbone yields more substantial benefits than representation conditioning when effective geometric signals are available. We attribute this to the fact that representation conditioning does not explicitly warm up physics learning, limiting its effectiveness.

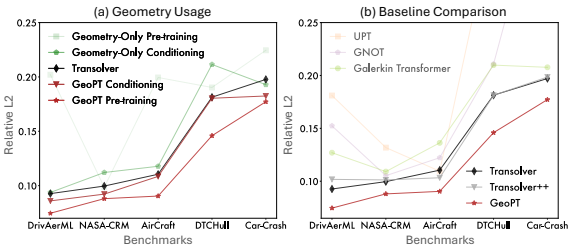


Figure 8: (a) Analysis for the geometry usage, including geometry-only v.s. dynamics-lifted spaces and pre-training v.s. conditioning. (b) Backbone comparison.

Backbone selection. In GeoPT, we adopt Transolver (Wu et al., 2024) as the default backbone and compare it with other Transformer-based neural simulators. As shown in Fig. 8(b), under training-from-scratch settings, Transolver consistently outperforms other baseline models in most benchmarks, justifying our choice of backbone. These results further confirm the effectiveness of GeoPT, showing consistent improvements even on advanced benchmarks.

Generalize to other physics domains. GeoPT is pre-trained with highly diverse dynamics, endowing it with strong potential to generalize across physics domains. We apply GeoPT to radiosity simulation (Goral et al., 1984), a classical light transport problem, which involves fundamentally different governing physics and geometries from our main experiments. Despite a significant domain shift, GeoPT continues to yield consistent performance improvements, which achieves an MAE of 9.0×10^{-2}, outperforming training from scratch (9.7×10^{-2}). Qualitatively, Fig. 9 reveals that GeoPT captures high-frequency shadow boundaries more accurately, particularly in regions with complex light-geometry interactions. More implementation details of this task are in Appendix E.1.

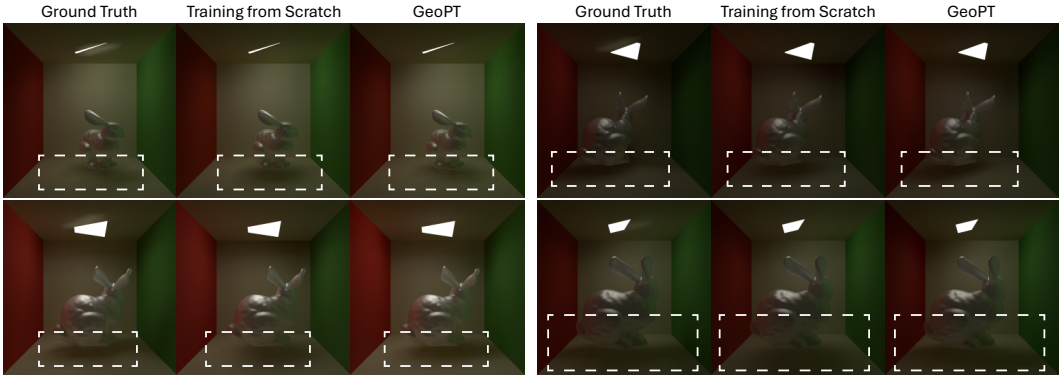


Figure 9: Neural radiosity simulation on Cornell box with Stanford bunny. GeoPT captures high-frequency shadow boundaries (dashed boxes) more accurately than training from scratch.

6 Conclusion

This paper presents GeoPT in pursuit of a unified pre-trained model for general physics simulation. Trained solely on geometry data with dynamics-lifted supervision, GeoPT consistently improves diverse downstream physics tasks, while significantly reducing training data requirements and accelerating convergence. GeoPT also presents favorable scalability w.r.t. data and model size, demonstrating a possible pathway for scaling neural simulators. As future work, we will further investigate the scaling behavior of GeoPT by continuously expanding the pre-training data and increasing model capacity, as well as validating its effectiveness on broader physical systems.

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REFERENCES

Josh Achiam, Steven Adler, Sandhini Agarwal, Lama Ahmad, Ilge Akkaya, Florencia Leoni Aleman, Diogo Almeida, Janko Altenschmidt, Sam Altman, Shyamal Anadkat, et al. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023.

Benedikt Alkin, Andreas Fürst, Simon Schmid, Lukas Gruber, Markus Holzleitner, and Johannes Brandstetter. Universal physics transformers: A framework for efficiently scaling neural operators. *NeurIPS*, 2024.

Altair Engineering Inc. Altair physicsai. `https://www.altair.com/physicsai`, 2026a. Accessed: 2026-01-06.

Altair Engineering Inc. Altair radioss. `https://www.openradioss.org`, 2026b. Accessed: 2026-01-06.

Ansys Inc. Ansys simai. `https://www.ansys.com/products/simai`, 2026. Accessed: 2026-01-06.

Neil Ashton, Charles Mockett, Marian Fuchs, Louis Fliessbach, Hendrik Hetmann, Thilo Knacke, Norbert Schonwald, Vangelis Skaperdas, Grigoris Fotiadis, Astrid Walle, et al. Drivaerml: High-fidelity computational fluid dynamics dataset for road-car external aerodynamics. *arXiv preprint arXiv:2408.11969*, 2024.

Noah J Bagazinski and Faez Ahmed. Ship-d: Ship hull dataset for design optimization using machine learning. In *IDETC-CIE*. American Society of Mechanical Engineers, 2023.

Philipp Bekemeyer, Nathan Hariharan, Andrew M Wissink, and Jason Cornelius. Introduction of applied aerodynamics surrogate modeling benchmark cases. In *AIAA SCITECH 2025 Forum*, 2025.

Shuhao Cao. Choose a transformer: Fourier or galerkin. In *NeurIPS*, 2021.

Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *ICCV*, 2021.

Angel X Chang, Thomas Funkhouser, Leonidas Guibas, Pat Hanrahan, Qixing Huang, Zimo Li, Silvio Savarese, Manolis Savva, Shuran Song, Hao Su, et al. Shapenet: An information-rich 3d model repository. *arXiv preprint arXiv:1512.03012*, 2015.

Tianqi Chen, Bing Xu, Chiyuan Zhang, and Carlos Guestrin. Training deep nets with sublinear memory cost. *arXiv preprint arXiv:1604.06174*, 2016.

Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. A simple framework for contrastive learning of visual representations. In *ICML*, 2020.

Krzysztof Choromanski, Valerii Likhosherstov, David Dohan, Xingyou Song, Andreea Gane, Tamás Sarlós, Peter Hawkins, Jared Davis, Afroz Mohiuddin, Lukasz Kaiser, David Belanger, Lucy J. Colwell, and Adrian Weller. Rethinking attention with performers. *ICLR*, 2021.

Matt Deitke, Dustin Schwenk, Jordi Salvador, Luca Weihs, Oscar Michel, Eli VanderBilt, Ludwig Schmidt, Kiana Ehsani, Aniruddha Kembhavi, and Ali Farhadi. Objaverse: A universe of annotated 3d objects. In *CVPR*, 2023.

Lawrence C Evans. *Partial differential equations*. American Mathematical Soc., 2010.

Lawrence C. Evans. First-order partial differential equations. In *Partial Differential Equations*, chapter 3. American Mathematical Society, 2022.

Olivier Faugeras and José Gomes. Dynamic shapes of arbitrary dimension: the vector distance functions. In *The Mathematics of Surfaces IX: Proceedings of the Ninth IMA Conference on the Mathematics of Surfaces*. Springer, 2000.

Cindy M Goral, Kenneth E Torrance, Donald P Greenberg, and Bennett Battaile. Modeling the interaction of light between diffuse surfaces. *ACM SIGGRAPH*, 1984.

Zhongkai Hao, Chengyang Ying, Zhengyi Wang, Hang Su, Yinpeng Dong, Songming Liu, Ze Cheng, Jun Zhu, and Jian Song. Gnot: A general neural operator transformer for operator learning. *ICML*, 2023.

Zhongkai Hao, Chang Su, Songming Liu, Julius Berner, Chengyang Ying, Hang Su, Anima Anandkumar, Jian Song, and Jun Zhu. Dpot: Auto-regressive denoising operator transformer for large-scale pde pre-training. *ICML*, 2024.

Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. Momentum contrast for unsupervised visual representation learning. In *CVPR*, 2020.

Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. In *CVPR*, 2022.

Maximilian Herde, Bogdan Raonic, Tobias Rohner, Roger Käppeli, Roberto Molinaro, Emmanuel de Bézenac, and Siddhartha Mishra. Poseidon: Efficient foundation models for pdes. *NeurIPS*, 2024.

Benjamin Holzschuh, Georg Kohl, Florian Redinger, and Nils Thuerey. P3d: Scalable neural surrogates for high-resolution 3d physics simulations with global context. *arXiv preprint arXiv:2509.10186*, 2025.

Po-Yao Huang, Hu Xu, Juncheng Li, Alexei Baevski, Michael Auli, Wojciech Galuba, Florian Metze, and Christoph Feichtenhofer. Masked autoencoders that listen. *NeurIPS*, 2022.

Hrvoje Jasak. Openfoam: Open source cfd in research and industry. *JNAOE*, 2009.

Nikola Kovachki, Zongyi Li, Burigede Liu, Kamyar Azizzadenesheli, Kaushik Bhattacharya, Andrew Stuart, and Anima Anandkumar. Neural operator: Learning maps between function spaces with applications to pdes. *JMLR*, 2023.

Zijie Li, Dule Shu, and Amir Barati Farimani. Scalable transformer for pde surrogate modeling. *NeurIPS*, 2023a.

Zongyi Li, Nikola Borislavov Kovachki, Kamyar Azizzadenesheli, Burigede liu, Kaushik Bhattacharya, Andrew Stuart, and Anima Anandkumar. Fourier neural operator for parametric partial differential equations. In *ICLR*, 2021.

Zongyi Li, Daniel Zhengyu Huang, Burigede Liu, and Anima Anandkumar. Fourier neural operator with learned deformations for pdes on general geometries. *JMLR*, 2023b.

Zongyi Li, Nikola Borislavov Kovachki, Chris Choy, Boyi Li, Jean Kossaifi, Shourya Prakash Otta, Mohammad Amin Nabian, Maximilian Stadler, Christian Hundt, Kamyar Azizzadenesheli, et al. Geometry-informed neural operator for large-scale 3d pdes. *arXiv preprint arXiv:2309.00583*, 2023c.

Zeming Lin, Halil Akin, Roshan Rao, Brian Hie, Zhongkai Zhu, Wenting Lu, Nikita Smetanin, Robert Verkuil, Ori Kabeli, Yaniv Shmueli, et al. Evolutionary-scale prediction of atomic-level protein structure with a language model. *Science*, 2023.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. In *ICLR*, 2019.

Huakun Luo, Haixu Wu, Hang Zhou, Lanxiang Xing, Yichen Di, Jianmin Wang, and Mingsheng Long. Transolver++: An accurate neural solver for pdes on million-scale geometries. In *ICML*, 2025.

Mohammad Amin Nabian, Sudeep Chavare, Deepak Akhare, Rishikesh Ranade, Ram Cherukuri, and Srinivas Tadepalli. Automotive crash dynamics modeling accelerated with machine learning. *arXiv preprint arXiv:2510.15201*, 2025.

Adam Paszke, S. Gross, Francisco Massa, A. Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Z. Lin, N. Gimelshein, L. Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zach DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. Pytorch: An imperative style, high-performance deep learning library. In *NeurIPS*, 2019.

Eric Perlman, Randal Burns, Yi Li, and Charles Meneveau. Data exploration of turbulence simulations using a database cluster. In *Supercomputing*, 2007.

Tobias Pfaff, Meire Fortunato, Alvaro Sanchez-Gonzalez, and Peter Battaglia. Learning mesh-based simulation with graph networks. In *ICLR*, 2021.

Md Ashiqur Rahman, Zachary E Ross, and Kamyar Azizzadenesheli. U-no: U-shaped neural operators. *TMLR*, 2023.

Maziar Raissi, Alireza Yazdani, and George Em Karniadakis. Hidden fluid mechanics: Learning velocity and pressure fields from flow visualizations. *Science*, 2020.

Rohan Sawhney. Fcpw: Fastest closest points in the west, 2021.

Leslie N Smith and Nicholay Topin. Super-convergence: Very fast training of neural networks using large learning rates. In *Artificial intelligence and machine learning for multi-domain operations applications*. SPIE, 2019.

Pavel Ŝolín. *Partial differential equations and the finite element method*. John Wiley & Sons, 2005.

Hunyuan3D Team Tencent. Hunyuan3d 2.0: Scaling diffusion models for high resolution textured 3d assets generation, 2025.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *NeurIPS*, 2017.

Pascal Vincent, Hugo Larochelle, Yoshua Bengio, and Pierre-Antoine Manzagol. Extracting and composing robust features with denoising autoencoders. In *ICML*, 2008.

Hanchen Wang, Tianfan Fu, Yuanqi Du, Wenhao Gao, Kexin Huang, Ziming Liu, Payal Chandak, Shengchao Liu, Peter Van Katwyk, Andreea Deac, et al. Scientific discovery in the age of artificial intelligence. *Nature*, 2023.

Gege Wen, Zongyi Li, Kamyar Azizzadenesheli, Anima Anandkumar, and Sally M Benson. U-fno–an enhanced fourier neural operator-based deep-learning model for multiphase flow. *Advances in Water Resources*, 2022.

Shizheng Wen, Arsh Kumbhat, Levi Lingsch, Sepehr Mousavi, Yizhou Zhao, Praveen Chandrashekar, and Siddhartha Mishra. Geometry aware operator transformer as an efficient and accurate neural surrogate for pdes on arbitrary domains. *arXiv preprint arXiv:2505.18781*, 2025.

Haixu Wu, Tengge Hu, Huakun Luo, Jianmin Wang, and Mingsheng Long. Solving high-dimensional pdes with latent spectral models. In *ICML*, 2023.

Haixu Wu, Huakun Luo, Haowen Wang, Jianmin Wang, and Mingsheng Long. Transolver: A fast transformer solver for pdes on general geometries. In *ICML*, 2024.

Zhenda Xie, Zheng Zhang, Yue Cao, Yutong Lin, Jianmin Bao, Zhuliang Yao, Qi Dai, and Han Hu. Simmim: A simple framework for masked image modeling. In *CVPR*, 2022.

Liu Yang, Siting Liu, Tingwei Meng, and Stanley J. Osher. In-context operator learning with data prompts for differential equation problems. *PNAS*, 2023.

Zhanhong Ye, Xiang Huang, Leheng Chen, Hongsheng Liu, Zidong Wang, and Bin Dong. Pdeformer: Towards a foundation model for one-dimensional partial differential equations. *arXiv preprint arXiv:2402.12652*, 2024.

Xumin Yu, Lulu Tang, Yongming Rao, Tiejun Huang, Jie Zhou, and Jiwen Lu. Point-bert: Pre-training 3d point cloud transformers with masked point modeling. In *CVPR*, 2022.

Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. In *CVPR*, 2023.

Zhizhou Zhang, Youjia Wu, Kaixuan Zhang, and Yanjia Wang. From cheap geometry to expensive physics: Elevating neural operators via latent shape pretraining. *arXiv preprint arXiv:2509.25788*, 2025.

Hang Zhou, Yuezhou Ma, Haixu Wu, Haowen Wang, and Mingsheng Long. Unisolver: Pde-conditional transformers towards universal neural pde solvers. In *ICML*, 2025.

Tingtao Zhou, Xuan Wan, Daniel Zhengyu Huang, Zongyi Li, Zhiwei Peng, Anima Anandkumar, John F Brady, Paul W Sternberg, and Chiara Daraio. Ai-aided geometric design of anti-infection catheters. *Science Advances*, 2024.

A THEORETICAL UNDERSTANDING OF GEOPT PRE-TRAINING

This section provides a theoretical interpretation of tracking moving particles in terms of transport equations (also called the collisionless Boltzmann equation or Liouville's equation). We will show that *(i)* tracking a large number of particle trajectories with fixed transport directions is equivalent to solving a transport equation with sticking boundary conditions, and that *(ii)* the resulting dynamics satisfy a natural mass conservation property in the phase space.

Dynamics process restatement Here, we recap the dynamics defined in GeoPT. Let $\Omega \subset \mathbb{R}^C$ denote the open computational domain. In GeoPT pre-training (Eq. 6 of main text), we consider an ensemble of particles initialized with positions $\mathbf{x}_0$ sampled from the computation domain and the geometry boundary and assigned transport directions $\mathbf{v} \sim \mathrm{Unif}(\mathbb{B}^C)$, which remain constant throughout the evolution. Under this setting, each particle follows a free-flight trajectory

$$\mathbf{x}(t) = \mathbf{x}_0 + t\,\mathbf{v}, \qquad t \geq 0. \tag{9}$$

When a particle reaches geometry boundary G, it sticks to G and remains there permanently.

Phase-space transport formulation Since in GeoPT, each tracking particle carries both a position and a transport direction, the most natural continuum description is given in phase space. Let $f(x, v, t)$ denote the phase-space density of particles at position x, velocity v, and time t. Then, under dynamics in Eq. 9, f satisfies the collisionless transport equation, which can be formalized as follows

$$\partial_t f(x, v, t) + v \cdot \nabla_x f(x, v, t) = 0, \qquad (x, v) \in \Omega \times \mathbb{R}^C. \tag{10}$$

It can be proved that, Eq. 10 describes advection in phase space along characteristic curves (2022)

$$\dot{\mathbf{x}}(t) = \mathbf{v}, \qquad \dot{\mathbf{v}}(t) = 0, \tag{11}$$

which correspond exactly to the particle trajectories defined in Eq. 9. Therefore, sampling particle trajectories and recording pairs $(x(t), v)$ therefore amounts to sampling characteristic curves of the phase-space transport equation.

Besides, the sticking behavior at the boundary is modeled by allowing particles to transfer from the interior phase space to a boundary-supported phase-space density. Let $f_G(x, v, t)$ denote the phase-space density of particles accumulated on G. The flux of particles reaching the boundary is given by $(v \cdot n(x))f(x, v, t)$, where $n(x)$ denotes the outward unit normal. Only particles with $v \cdot n(x) > 0$ reach the boundary. Accordingly, the boundary accumulation satisfies

$$\partial_t f_G(x, v, t) = (v \cdot n(x))_+ \, f(x, v, t)\, dv, \qquad x \in G. \tag{12}$$

In summary, Eq. 10 and 12 together define a transport equation with the sticking boundary, which is the continuum limit of GeoPT self-supervision formalized in Eq. 6.

Proposition A.1 (**Mass conservation**). *The phase-space transport equation in Eq. 10 is conservative. In the absence of sticking, the phase-space flow $(x, v) \mapsto (x + tv, v)$ is divergence-free. With sticking boundaries, mass is not destroyed but transferred from the interior to the boundary. Specifically, the total phase-space mass satisfies (see, e.g., (Evans, 2010))*

$$\frac{d}{dt}\left(\int_\Omega \int_{\mathbb{R}^d} f(x, v, t)\, dv\, dx + \int_G \int_{\mathbb{R}^d} f_G(x, v, t)\, dv\, dS(x)\right) = 0. \tag{13}$$

Here $dS(x)$ denotes the surface measure on $G = \partial\Omega$. Thus, the dynamics conserve the total number of particles globally, with mass redistributed from the interior to the boundary.

Remark A.2 (**Connect between GeoPT pre-training and solving collisionless transport equation in Eq. 10**). In the above analysis, we have demonstrated that the final phase-space density function f of the constructed dynamic process follows the collisionless transport equation. And, in GeoPT, we input the spatial and velocity coordinates of all sampled tracking points into a neural network and supervised the model with L2 loss to predict the dynamic process. Since the dynamic supervision is defined in Eq. 4, which can be seen as a temporal discretization of $f(x, v, t)$, the learning process of GeoPT is actually to estimate $f(x, v, t)$ from the corresponding spatial and velocity coordinates.

As stated in proposition A.1, the flow density f that is used as a self-supervision signal obeys mass conservation under all kinds of velocity settings. During the pre-training process, we randomly sample geometries g and velocity fields $\mathbf{v}$ as the model input. Beyond ensuring data diversity, the above-described pre-training will enforce the model output maintain the mass conservation law under all kinds of geometries and dynamics.

Remark A.3 (**Generalizability of theoretical framework**). The phase-space transport equation captures a canonical conservation-law structure: mass evolves by advection along characteristics, with boundary flux accounting. Many physical models can be viewed as augmentations of this structure. For example, the Boltzmann equation adds a collision operator to the streaming term, and fluid equations such as Navier-Stokes couple mass conservation with additional momentum and constitutive relations. Consequently, while our pre-training signal is derived from a simplified transport process, it instills an inductive bias toward characteristic-driven correlations and boundary interactions, which are shared components across a broad class of continuum and kinetic systems. We therefore expect the pre-trained representation to transfer to downstream PDE solvers after task-specific adaptation, rather than guaranteeing universal generalization by itself.

B Pre-Training Investigation

This section provides the investigation of GeoPT's pre-training configurations in the dataset, dynamics and geometry supervision signals.

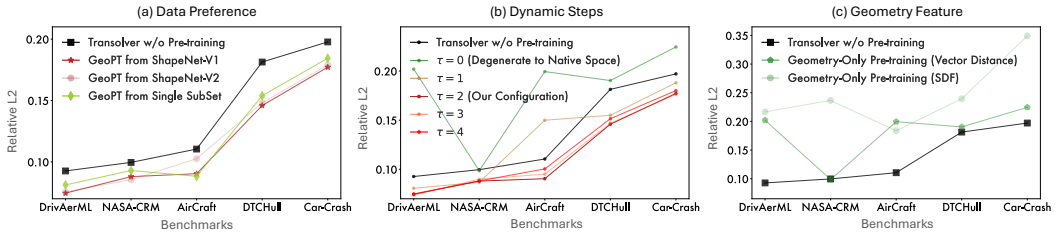


Figure 10: Ablations for pre-training choices in GeoPT, including the comparison among (a) pre-training with a single subset or mixed data from ShapeNet-V1, -V2, (b) discretizing the dynamics into various step numbers τ, and (c) pre-training with different geometry information, such as SDF and vector distance. All the experiments are based on GeoPT-Based under the full-data-training setting.

Ablation 1: single v.s. mixed geometry dataset In GeoPT, we attempt to build a unified pre-trained model for all types of physics simulations. Thus, the default setting in GeoPT is to use a mix of cars, airplanes, and watercraft as the pre-training dataset. However, it is also possible to adopt GeoPT on a case-by-case basis, such as pre-training only on the car subset for DrivAerML and Car-Crash simulation, only on the airplane subset for NASA-CRM and AirCraft, and only on the watercraft subset for DTCHull, which can better align with the geometry in the downstream task. We have also compared GeoPT with the single-subset pre-training setting in Fig. 10(a) red v.s. green curves. It is observed that in most tasks, a more diverse pre-training brings better performance, highlighting the value of unified pre-training. Only for AirCraft, single-subset pre-training is slightly better. Notably, this task can be viewed as a corner case, which contains quite different geometries w.r.t. the pre-training geometries (Fig. 16), thereby involving cars or watercraft that are far away from AirCraft geometries in pre-training may cause distraction. One possible solution is to keep enlarging the diversity of pre-training geometries.

Ablation 2: ShapeNet-V1 (low quality but high diversity) v.s. ShapeNet-V2 (high quality but low diversity) In the official configuration of GeoPT, we adopt the ShapeNet-V1 (Chang et al., 2015) for pre-training, which contains 13,463 geometries in total for car, watercraft and airplane categories. However, geometries in the initial version of ShapeNet may contain incorrect normals and non-aligned orientations. ShapeNet-V2 is an updated version with manually corrected meshes, normals, and normalized orientations, but it contains only 9,515 geometries in the three industrial-related categories. In Fig. 10(a), we compare the performance of GeoPT pretrained from ShapeNet-V1 and -V2. It is observed that in most benchmarks, ShapeNet-V1 pre-training brings better performance, even though it is based on geometries without careful quality control. This finding also highlights the importance of geometry diversity, encouraging the wide collocation of 3D geometries, where the advanced 3D generation models can be a good data source (Tencent, 2025).

Ablation 3: step number in dynamics configuration As described before, we discretize the dynamic process into $(\tau + 1)$ steps, which generates the dynamic trajectory supervision $\boldsymbol{h}_G(\mathbf{x}_{0:\tau}) \in \mathbb{R}^{(\tau+1)\times C}$. As presented in Fig. 10(b), $\tau = 0$ corresponds to the degeneration scenario, which

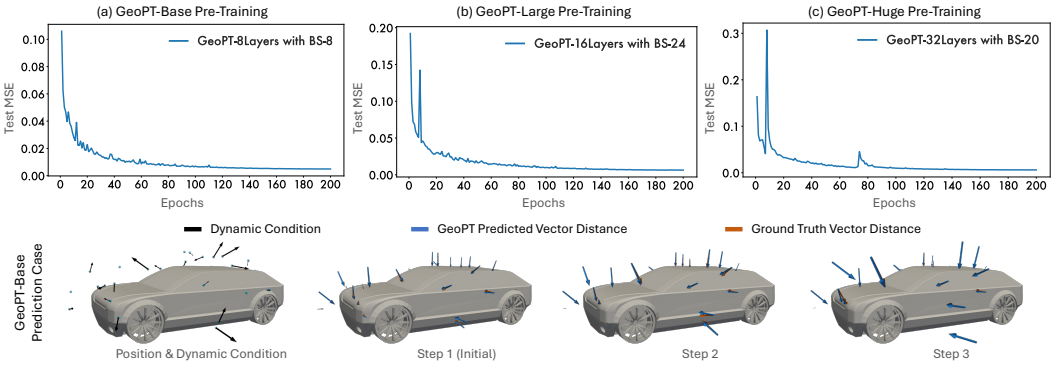


Figure 11: The pre-training process of GeoPT. (a) We plot the test MSE change during 200 pre-training epochs, which is calculated on 300 leave-out geometries. The initial unstable stage is caused by *learning rate warm up*. (b) Prediction case of the pre-trained GeoPT-Base. For clarity, we only plot 35 points under 3 dynamic steps, where the prediction is in blue and the ground truth is in orange.

is still the static geometry supervision, thereby cannot bring benefits to physics simulation. One step forward, namely $\tau = 1$, is able to bring a significant promotion, highlighting the necessity of dynamics representation. In general, $\tau = 2$ achieves a balanced performance across various physics simulation tasks, which is also set as our default configuration. Besides, adding dynamic steps will not consistently bring benefits since the accumulated discretization error, which is why $\tau = 3, 4$ can only surpass the default configuration in part of the benchmarks. It is also worth noting that increasing τ will also cause more computation costs. Thus, $\tau = 2$ is a well-verified choice.

Ablation 4: vector distance v.s. SDF in choosing geometry feature In the main text, we have compared with pre-training with vector-distance-based geometry-only supervision. It is also applicable to adopt SDF as the supervision. However, as shown in Fig. 10(c), SDF supervision is generally worse than vector distance. This result may be because vector distance is more informative than SDF for each point, which not only contains distance information but also involves the direction. Based on this result, in GeoPT, we also adopt vector distance as $\boldsymbol{h}_G(\cdot)$ in Eq. 5 to encode the geometry.

Pre-training visualization To provide an intuitive understanding of GeoPT pre-training, we plot the test loss curve in Fig. 11, where GeoPT with different sizes all converge smoothly. Specifically, the relatively unstable curve for the early stage during pre-training is caused by learning rate warm-up. Besides, Fig. 11 also presents the prediction results for self-supervised dynamic processes. Specifically, the initial geometry information and dynamics field are input to GeoPT and the model is expected to predict the vector distance w.r.t. the geometry surface for the future three steps. We can find that the pre-trained GeoPT can precisely predict the future dynamics, indicating sufficient optimization in pre-training.

C Fine-Tuning Investigation

This section provides the analysis for the usage and special features of GeoPT during fine-tuning.

Fine-tuning configuration for particle velocity As described in the main text, we need to parameterize the simulation setting into particle velocity V_S for GeoPT fine-tuning. Specifically, we need to determine both the direction and norm:

- As for the direction of the particle velocity V_S, the configuration is quite certain in practice, which can be directly calculated based on the direction of incoming flow in aerodynamics (*e.g.*, yaw angle in DTCHull or angle of attack and sideslip in AirCraft) or force direction in solid mechanics (*e.g.*, impact angle of Car-Crash).
- As for the norm of the particle velocity V_S, corresponding to speed, it needs more calibrations, since the pre-training is based on the normalized geometry and normalized moving speed, while the simulation speed is a real-world value. Therefore, a correspondence between the normalized geometry space and the real-world physics space is expected.

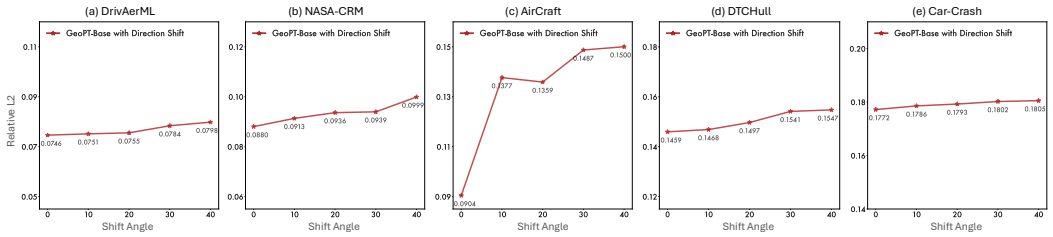


Figure 12: GeoPT-Base performance change w.r.t. the direction *shifted* (by 0° to 40°) from the correct configuration. Zero shift refers to configuring the dynamics field direction along the incoming flow or impact angle, which is our default setting. For clarity, we adopt the same y-axis range of 0.75 among different benchmarks in visualization. All experiments are under the full-data-full-training setting.

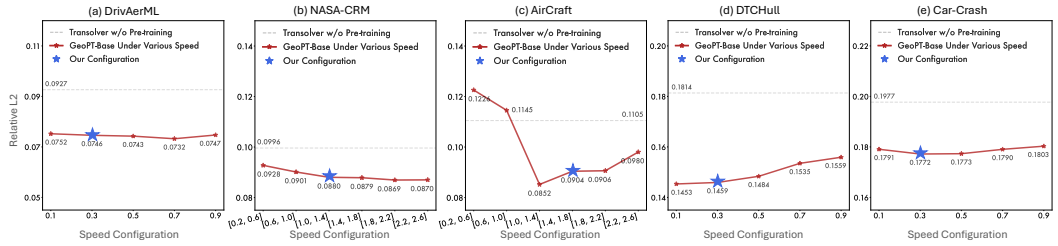


Figure 13: GeoPT-Base performance change w.r.t. the *configured velocity norm in* V_S, which is sampled from $[0, 2]$ during pre-training. For real-world low-speed cases, such as car and watercraft simulations, we explore the choices within less than 1.0. As for high-speed cases, such as aircraft, we explore a larger range $[0.2, 2.6]$. Since both NASA-CRM and AirCraft involve varying simulation speeds, we normalize the real-world configuration into different intervals. All the experiments are under the full-data-full-training setting.

In our experiments, we do not elaborately tune the configuration of V_S, especially for its norm. To give an intuitive understanding and practical recipe for fine-tuning configurations, we provide a detailed analysis here.

(i) Performance under direction shift. Fig. 12 demonstrates that directly adopting the incoming flow or impact direction from downstream simulation settings achieves the best performance, which corresponds to the zero shift setting. Although globally shifting the direction configuration by a fixed value can also ensure a quantitatively distinguishable condition value among different samples for the model, it will cause performance degradation since it will inform the pre-trained with incorrect correlations, as visualized in Fig. 7(c). Therefore, the performance drop gets more serious under a larger direction shift. Specifically, the performance drop is more significant for high-speed scenarios, such as NASA-CRM and AirCraft, because their high-speed configuration will magnify the effect of incorrect configuration of direction.

(ii) Performance under various speed configurations. To ensure a precise alignment between pre-training supervision and fine-tuning configuration, we need to consider all the simulation settings, such as object length, flow viscosity, and real-world speed, to determine the norm of V_S. However, in practice, we find that a roughly reasonable speed configuration is sufficient to deliver a fair performance. In our experiments, we set the norm of elements in V_S as 0.3 for all low-speed scenarios, including DrivAerML, DTCHull and Car-Crash[2] and normalize the real-world speed in NASA-CRM and AirCraft into an interval with larger values, which is $[1.0, 1.4]$ and $[1.4, 1.8]$, respectively. In general, as presented in Fig. 13, the low-speed scenarios prefer smaller speed configurations and the high-speed task requires a V_S with a larger norm, as the latter usually corresponds to more concentrated physical states, which can be "prompted" by a larger speed configuration (Fig. 7(c)).

Based on the above analysis, we summarize the following usage recipe for GeoPT.

[2]In this paper, we configure the dynamics field in Car-Crash with a linearly decayed norm. Here, we only consider the maximum speed value. If we adopt the same speed value for all elements, there will be a slight performance drop, where the relative L2 is 0.1783.

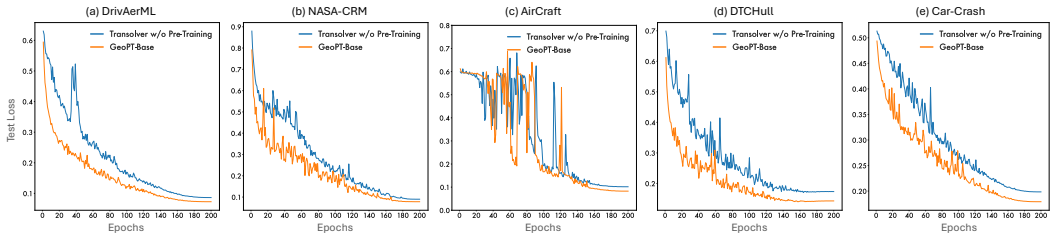


Figure 14: Test loss (relative L2) change during fine-tuning. Note that these test losses are calculated from the downsampled physics field to ensure training efficiency, which is proportional to the final performance, but may be shifted w.r.t. the full mesh results.

Configuration recipe for dynamics conditions V_S. *In general, the direction of the velocity field should be set following the simulation settings, while the norm of velocity can be set within* $[0.1, 1.0]$ *for commonly seen low-speed simulations, such as driving cars or ships with speed less than 100 m/s, and be set within* $[1.0, 2.0]$ *for high-speed tasks.*

Remark C.1 (**Distinguishable configurations**). It is worth noticing that without pre-training, the dynamics configuration only needs to be distinguishable to reflect simulation configurations since the model will automatically learn to project the input into deep representations. In GeoPT, we pursue a suitable dynamics configuration to align the pre-training model and the downstream task, where different dynamics configurations activate different correlation patterns (Fig. 7(c)), while the effective range of configuration is quite flexible as the model can be further optimized during finetuning.

Fine-tune loss curves We also plot the test loss during the fine-tuning in Fig. 14, where GeoPT can consistently improve the convergence performance and help to accelerate the training stability, especially for the early stage, such as DrivAerML and DTCHull. Note that the physics simulation task evaluated in this paper is quite challenging, which requires the model to infer the whole physics field solely from geometry information and simulation settings. Therefore, the training processes of all benchmarks are not very stable in the early stage, but will converge smoothly in the end.

As for the AirCraft benchmark that involves a serious out-of-domain generalization challenge due to the training-test geometry gap, the training process is not very stable as presented in Fig. 14(c), where we have also tried $10\times$ smaller learning rates, but still cannot ensure a smooth convergence, indicating the learning difficulty of this task. Still, in this task, GeoPT can improve the final convergence performance, highlighting its effectiveness.

D SHOWCASES

As a supplement to Fig. 7, we plot the showcases from the other four benchmarks in Fig. 15-18.

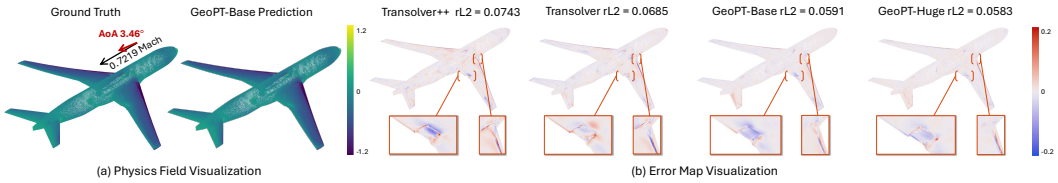


Figure 15: Showcase of NASA-CRM. (a) The pressure coefficient field of the airplane flying under 0.7219 Mach and 3.46° angle of attack. (b) Error map and the relative L2 of different models for this case. For clarity, we zoom in on high-error zones.

As presented in the first subfigure, GeoPT can accurately predict the physics field of challenging simulation tasks, which involve complex geometries and diverse simulation settings. For example, in AirCraft, the model needs to predict six aerodynamic forces and moments simultaneously and this task contains four variables for different cases: geometry, speed, angle of attack and sideslip, making the prediction extremely challenging, while GeoPT can bring over 10% improvement over Transolver trained from scratch and consistently benefits from model scaling.

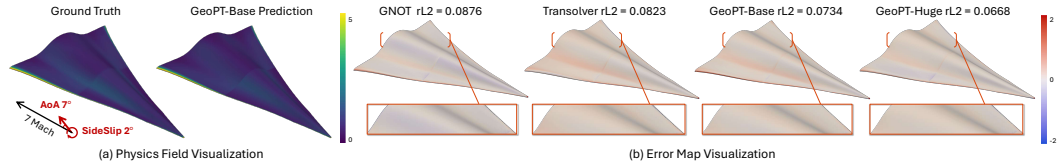


Figure 16: Showcase of AirCraft. We plot the Z-force coefficient field for aircraft flying under 7 Mach, 7° angle of attack and 2° sideslip.

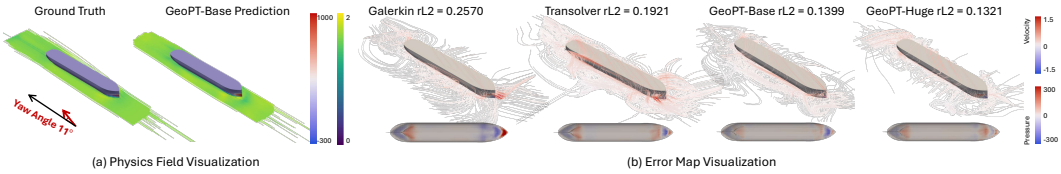


Figure 17: Showcase of DTCHull. (a) We plot the hydrostatic pressure–corrected pressure and surrounding velocity streamlines for a ship moving under 11° yaw angle. (b) We highlight the surrounding velocity error in the streamline and the pressure error in underside view.

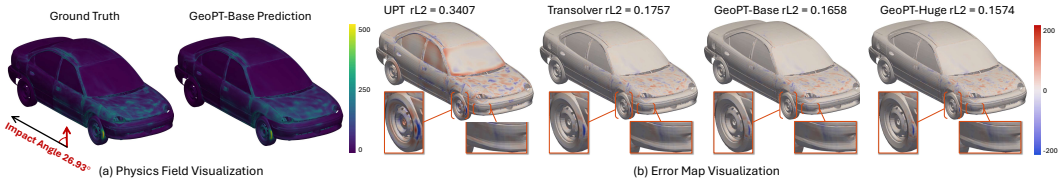


Figure 18: Showcase of Car-Crash. We plot the element-wise maximum 2D Von Mises stress during the crash with 26.93° impact angle.

As for DTCHull and Car-Crash, both tasks involve intricate physical interactions, where the former requires the model to predict the water-air two-phase interactions and the latter needs to predict the maximum stress during structure deformation caused by the crash. Especially for Car-Crash, the stress field can be discontinuous due to the fracture. In these two difficult tasks, lifted geometric pre-training can still improve the performance and significantly surpass the baselines.

E Implementation Details

This section will introduce implementation details for benchmark and data generation, training and baseline implementations.

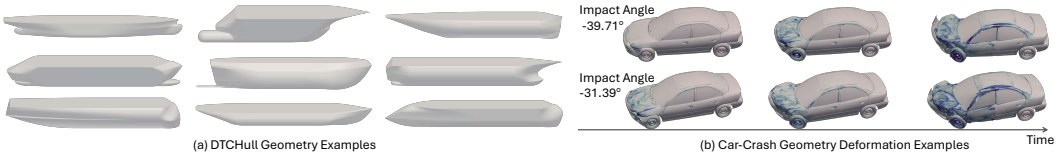
E.1 Benchmarks

We experiment with five industrial design tasks and one radiosity task to examine the model generalizability, where DrivAerML (Ashton et al., 2024), NASA-CRM (Bekemeyer et al., 2025) and AirCraft (Luo et al., 2025) are adopted from the previous work. We also newly simulate three benchmarks.

DTCHull This task is to simulate the ship resistance and wave-making process. First, we generate 130 different ship geometries by changing the hull parameterization script from (Bagazinski & Ahmed, 2023), which makes it easy to produce diverse geometries (Fig. 19). Then, we simulate the two-phase incompressible free-surface flow of water and air surrounding different ship geometries for 50 seconds using the Volume-of-Fluid (VoF) multiphase solver in OpenFOAM (Jasak, 2009), with constant fluid properties ($\rho_{\text{water}} = 998.8$, $\nu_{\text{water}} = 1.09 \times 10^{-6}$; $\rho_{\text{air}} = 1$, $\nu_{\text{air}} = 1.48 \times 10^{-5}$). The air–water interface is initialized as a flat surface located at 0.244 above the zero x–y plane, and we neglect surface tension. Turbulence is modeled with Reynolds-averaged Navier-Stokes (RANS) using the $k - \omega$ Shear Stress Transport model closure.

Table 2: Summary of experimental simulations. #Mesh records the size of the discretized meshes for each sample. #Variable records the varied simulation configurations among different samples. #Train and #Test represent the number of training and test samples.

Type	Benchmarks	#Mesh	#Variable	#Size	#Train	#Test	Output Physics
Aero-dynamics	DrivAerML	∼160M	Geometry	∼6TB	100	20	Pressure & Velocity
	NASA-CRM	∼450k	Geo, Speed, AoA	∼3GB	105	44	Pressure Coefficient
	AirCraft	∼330k	Geo, Speed, AoA, Sideslip	∼7GB	100	50	Aerodynamic Six Components
Hydro-	DTCHull	∼240k	Geo, Yaw Angle	∼2GB	100	20	Time-Avg Pressure & Velocity
Crash	Car-Crash	∼1M	Impact Angle	∼8GB	100	30	Time-max 2D Von Mises stress



(a) DTCHull Geometry Examples (b) Car-Crash Geometry Deformation Examples

Figure 19: Examples from DTCHull and Car-Crash benchmarks, which involve diverse geometries and deformations, respectively.

We set the water velocity as a normalized value of 1.668 and the air velocity as zero at initialization, which roughly corresponds to a 12 m/s moving scenario in the real-world scale. For each case, we randomly sample a yaw angle from $[-10°, 10°]$ to mimic real-world diversity. Finally, we average the hydrostatic pressure–corrected pressure and surrounding velocity over the last 20 seconds as the target, when the dynamics are relatively stable.

Car-Crash This task is to simulate high-speed impact dynamics with large deformations, contact interactions, and potential material failure jointly determine the evolving vehicle geometry. We adopt the National Crash Analysis Center Neon model, a widely used full-vehicle crash benchmark with detailed part-level meshing and heterogeneous material assignments. Each simulation is carried out in OpenRadioss (Altair Engineering Inc., 2026b) using a 3D Lagrangian explicit finite-element formulation of transient momentum balance, where external loads and penalty-based contact forces are assembled at nodes and internal forces are computed element-by-element from stresses. At the element level, stresses are advanced by integrating the constitutive (material) law, including elastic/plastic response and, when enabled, damage/failure/erosion, driven by the local deformation.

For each run, we simulate 17 seconds of dynamics under a rigid-impact configuration, with an impact angle sampled uniformly from $[-45°, 45°]$, and record the maximum von Mises equivalent stress attained by each element over the entire trajectory. As shown in Fig. 19(b), although the initial geometry is fixed, varying the impact angle induces substantially different contact sequences and load paths, leading to distinct deformation and final geometry.

Radiosity To evaluate whether GeoPT transfers to physical regimes beyond those evaluated in our main experiments, we apply it to radiosity simulation (Goral et al., 1984), a classical light transport problem that computes global illumination by modeling diffuse inter-reflections between surfaces. This problem has fundamentally different governing physics from the fluid and solid mechanics tasks in our main experiments. We construct a dataset of 200 radiosity renderings in a Cornell box scene (Goral et al., 1984) with a Stanford bunny placed at varying positions and scales, illuminated by light sources with different intensities, sizes, and directions. We parameterize the dynamics conditions as the light propagation direction, analogous to the flow direction in aerodynamics. We finetune GeoPT on 160 training samples and evaluate on 40 held-out test samples. Notably, neither the Cornell box geometry nor any light transport physics was seen during pre-training. This benchmark examines GeoPT's potential as a general-purpose prior for diverse simulation tasks.

E.2 Self-Supervision Data

We provide the implementation details of self-supervision data generation in Algorithm 1. All three loops for geometry, dynamics and moving steps in the following algorithm can be executed in parallel.

Algorithm 1 Self-supervision data generation in GeoPT

Input Data: Geometry dataset $\mathcal{G}$
Input Config: Number of tracking points N, number of time steps τ, maximum velocity $v_{\max}$, number of velocity fields per geometry N_{dyn}
Output: Pre-training dataset $\mathcal{D}$ with $(N_{\text{dyn}} \times |\mathcal{G}|)$ samples
Initialize dataset $\mathcal{D} \leftarrow \emptyset$
for G **in** $\mathcal{G}$ **do**
  // **Step 1: Normalize geometry**
  $G \leftarrow \text{Rotate}(G)$ // Rotate geometry to align front face to $-x$ direction.
  $G \leftarrow \text{Shift}(G)$ // Zero-center x–y coordinates; place bottom on x-y plane.
  $G \leftarrow \text{Scale}(G)$ // Scale to unified x-axis length as 5.
  Build FCPW scene (2021) for G. Blue symbols indicate FCPW-accelerated operations.
  // **Step 2: Sample query positions**
  $\{\mathbf{x}\} \leftarrow \text{Sample}(\Omega_G \cup \partial G)$ // Sample from bounding box Ω_G and surface ∂G.
  $\{\mathbf{x}\} \leftarrow \text{Outside}(\{\mathbf{x}\}, G)$ // Remove points inside G; retain N tracking points.
  for i **in** $\{1, \ldots, N_{\text{dyn}}\}$ **do**
    // **Step 3: Sample synthetic velocity field**
    $\{\mathbf{v}\} \leftarrow \{\text{Sample}(\mathbb{B}^C)\}$ where $\mathbb{B}^C = \{\mathbf{v} \in \mathbb{R}^C : \|\mathbf{v}\|_2 \leq v_{\max}\}$ // Per-point i.i.d. sampling.
    // **Step 4: Compute feature trajectory following Eq. 4 and Eq. 5**
    Initialize trajectory $\boldsymbol{h}_G(\mathbf{x}_{0:\tau}) \leftarrow \emptyset$
    $\{\mathbf{x}_0\} \leftarrow \{\mathbf{x}\}$
    for t **in** $\{0, \ldots, \tau\}$ **do**
      $\boldsymbol{h}_G(\{\mathbf{x}_t\}) \leftarrow \text{VectorDistance}(\{\mathbf{x}_t\}, G)$ // Compute geometric features.
      Append $\boldsymbol{h}_G(\{\mathbf{x}_t\})$ to $\boldsymbol{h}_G(\{\mathbf{x}_{0:\tau}\})$
      $\{\mathbf{x}_{t+1}\} \leftarrow \text{Evolve}(\{\mathbf{x}_t\}, \{\mathbf{v}\}, G)$ // Update position: $\mathbf{x}_{t+1} = \mathbf{x}_t + \mathbf{v} \cdot \mathbb{1}_G(\mathbf{x}_t)$.
    end for
    Add $\{(\{\mathbf{x}\}, \{\mathbf{v}\}, G), \boldsymbol{h}_G(\mathbf{x}_{0:\tau})\}$ to $\mathcal{D}$
  end for
end for
Return $\boldsymbol{D} = \{(\{\mathbf{x}\}, \{\mathbf{v}\}, G), \boldsymbol{h}_G(\mathbf{x}_{0:\tau})\}$

E.3 Experiment Configuration

The detailed configurations can be found in Table 3. All the experiments are conducted in PyTorch (Paszke et al., 2019) on NVIDIA A100 40GB GPU. Gradient checkpointing (Chen et al., 2016) is used in the pre-training of GeoPT-large and -huge. We pre-train for 200 epochs using AdamW (Loshchilov & Hutter, 2019) with cosine annealing (He et al., 2022). For fine-tuning, we follow Transolver (Wu et al., 2024) and train for 200 epochs with AdamW and OneCycleLR scheduling (Smith & Topin, 2019) for each downstream physics simulation task.

Pre-training During pre-training, we only go through all the unique geometries in each epoch, which does not use all 100 dynamic trajectories for each geometry but randomly samples one from them within each epoch.

Fine-tuning For all methods, due to GPU memory limitations when processing extremely large geometries, we split the input mesh into several subsets with $50,000$-$100,000$ mesh points per subset and train the simulator on these downsampled geometries and physics fields. Regarding inference, we utilize the geometry-general property of Transformer solvers and directly infer the entire mesh at one forward pass, which is slightly more effective than separately inferring and then concatenating results in our experiments. Especially for the DrivAerML benchmark (Ashton et al., 2024) that contains 160M mesh points per sample, directly inferring the full mesh will cause out-of-memory. Therefore, in this benchmark, we split the surface mesh into 20 subsets and the volume mesh into 400 subsets at the beginning, and infer these subsets sequentially, where one volume subset is paired with one surface subset for inference.

E.4 Baselines

Here, we detail our implementation for baselines, including backbone selection and geometry usage.

Table 3: Configurations for GeoPT experiments. "B, L, H" represent the base, large and huge models.

(a) Self-supervision data configuration.

Terms	Configure
Used Geometry Data $\mathcal{G}$	
Car Subset	7,479 Shapes
Airplane Subset	4,045 Shapes
WaterCraft Subset	1,939 Shapes
Geometry bounding box to sampling tracking particles	
Car	$[-3.0, 4.2] \times [-1.5, 1.5] \times [0.0, 2.5]$
Airplane	$[-3.0, 4.5] \times [-2.8, 2.8] \times [0.0, 2.5]$
WaterCraft	$[-4.0, 5.0] \times [-1.5, 1.5] \times [-1.0, 1.0]$
Tracking particles N	
Volume	32,768
Surface	4,096
Dynamic process configuration	
number of steps τ	2
maximum velocity v_{max}	2
Dynamics per geometry	100
Pretraining samples	1,346,300 samples ($\sim$ 5TB)

(b) Training configurations.

Terms	Configure
Pre-Training Stage	
Optimizer	AdmaW (2019)
Base learning rate	0.001
Learning rate schedule	Cosine
Batch size	8 (B), 24 (L), 20 (H)
Warmup epochs	10
Total epochs	200
Loss function	L2 loss
Approx GPU Hours	144 (B), 360 (L), 576 (H)
Fine-Tuning Stage	
Optimizer	AdmaW (2019)
Base learning rate	0.001
Learning rate schedule	OneCycleLR
Batch size	1
Warmup epochs	PyTorch default
Total epochs	200
Loss function	Relative L2 loss
Approx GPU Hours	3 (B), 6 (L), 10 (H)

Backbone selection We adopt the implementation of Galerkin Transformer (Cao, 2021), GNOT (Hao et al., 2023) and Transolver (Wu et al., 2024) from the open-sourced repository Neural-Solver-Library[3], which provides high-quality implementations of various neural PDE solvers and has been verified by the authors of these papers. As for Transolver++ (Luo et al., 2025) and UPT (Alkin et al., 2024), we adopt their official code. For backbone comparison, we configure all the Transformer backbones as 8 layers with 256 hidden channels. Besides, we also adopt the same simulation parameterization proposed by GeoPT to incorporate condition information into these baselines.

Geometry usage Since prior research does not directly study geometric pre-training for physics, we compare GeoPT with two constructed baselines. Here are details for geometry usage baselines.

(i) Geometry-only pre-training. In this type of baseline, we only adopt the geometry-only feature as supervision. Specifically, we train the model to predict SDF or vector distance (Faugeras & Gomes, 2000) based on given positions.

Figure 20: Reconstruction examples of latent tokens extracted by Hunyuan3D.

(ii) Geometry-only conditioning. The prior work (Zhang et al., 2025) has explored using frozen geometry representation as the auxiliary information for PDE solving. However, the 3D model used in their work is limited to 3D inductors, which cannot be used in complex industrial designs tested in our paper. Thus, we adopt the advanced geometry model Hunyuan3D (Tencent, 2025) to extract the static geometry representation for comparison. Specifically, we adopt the pre-trained VAE model[4] encoder, which can receive a set of points sampled from a mesh geometry as input and encode it into 3,072 geometry tokens with 64 hidden channels. Then we integrate the extracted token sequence into Transolver based on an additional cross-attention layer to fuse the geometry tokens into input mesh representations, which is also the default usage in (Zhang et al., 2025). As shown in Fig. 20, the geometry representation learned by Hunyuan3D can precisely capture the detailed geometry information, thereby enabling accurate geometry reconstruction. However, as presented in the main results (Fig. 5), the static geometry representation cannot help the physics learning, even though it has already precisely encoded the geometry information.

[3]https://github.com/thuml/Neural-Solver-Library

[4]https://huggingface.co/tencent/Hunyuan3D-2/tree/main/hunyuan3d-vae-v2-0-withencoder

F FULL RESULTS

Align with existing benchmarks In this paper, we fix the training samples around 100 cases to mimic the industrial design practice. Here, we further conduct new experiments under aligned training settings with the two latest works: GAOT (Wen et al., 2025) and Transolver++ (Luo et al., 2025), to further benchmark GeoPT. As shown in Table 4, in the two largest datasets, DrivAerML (surface-only) and NASA-CRM, both Transolver and GeoPT surpass the previous benchmark by a large margin. As for AirCraft, GeoPT can also advance Transolver to the state-of-the-art performance. These results further justify the effectiveness of GeoPT, which consistently improves the model performance and achieves state-of-the-art.

Table 4: Comparison between GeoPT and the previous method under aligned training settings. The results directly adopted from the previous paper are marked as $*$, where the results in DrivAerML (surface-only) and NASA-CRM are both from GAOT (2025) and AirCraft is from Transolver++ (2025). † marks our implementation. (a-b) MSE and Mean AE are calculated on normalized values.

(a) DrivAerML (450 train samples)

Pressure Coe	MSE	Mean AE
GAOT* (2025)	0.051729	0.12352
GINO* (2023c)	0.088124	0.15238
Transolver*	*does not compare*	
Transolver†	0.004223	0.04125
GeoPT†	**0.003370**	**0.03617**

(b) NASA-CRM (105 train samples)

Pressure	MSE	Mean AE
GAOT* (2025)	0.077170	0.16014
GINO* (2023c)	0.105688	0.17450
Transolver*	*does not compare*	
Transolver†	0.011246	0.04938
GeoPT†	**0.010722**	**0.04456**

(c) AirCraft (140 training samples)

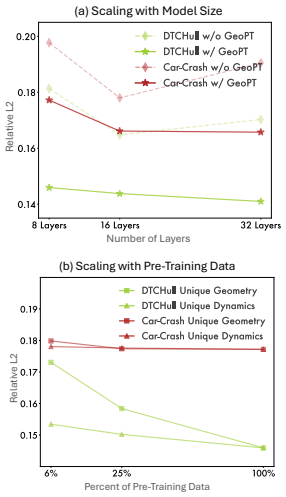
Aerodynamic Coes	relative L2
Transolver++* (2025)	0.064
GINO* (2023c)	0.133
Transolver*	0.092
Transolver†	0.083
GeoPT†	**0.062**

Scaling performance To supplement the scaling results in Fig. 6 of the main text, we further test the corresponding performance in DTCHull and Car-Crash in Table 5. It is also observed that pre-training with GeoPT can help avoid potential overfitting, especially in industrial design tasks where only limited data is available. Besides, GeoPT can also take advantage of diverse geometry and dynamics conditions, highlighting the value of rich 3D geometry assets.

Table 5: Quantitative results for scaling performance and supplement results in DTCHull and Car-Crash. Here "w/o GeoPT" refers to Transolver trained from scratch. "Unique Geo" and "Dyn" represent the use ratio of geometry data and sampled dynamics, respectively.

Model	Layers	DrivAerML	NASA-CRM	AirCraft	DTCHull	Car-Crash
w/o GeoPT	8	0.0927	0.0996	0.1104	0.1814	0.1977
w/o GeoPT	16	0.0847	0.0966	0.1160	0.1648	0.1779
w/o GeoPT	32	0.0839	0.0989	0.1153	0.1703	0.1905
GeoPT	8	0.0746	0.0880	0.0904	0.1459	0.1772
GeoPT	16	0.0702	0.0868	0.0864	0.1438	0.1661
GeoPT	32	0.0687	0.0851	0.0836	0.1410	0.1657

Model	Ratio	DrivAerML	NASA-CRM	AirCraft	DTCHull	Car-Crash
Unique Geo	6%	0.0819	0.0969	0.1102	0.1731	0.1798
Unique Geo	25%	0.0760	0.0902	0.0996	0.1584	0.1774
Unique Geo	100%	0.0746	0.0880	0.0904	0.1459	0.1772
Unique Dyn	6%	0.0760	0.0913	0.1097	0.1534	0.1781
Unique Dyn	25%	0.0755	0.0891	0.0954	0.1502	0.1776
Unique Dyn	100%	0.0746	0.0880	0.0904	0.1459	0.1772



Quantitative results Here, we present the concrete values in Tables 6-10 for five simulation tasks in Fig. 1 and 5. We color some results to highlight GeoPT's capability in improving performance, convergence and reducing data requirements:

(i) Improving performance: We color results that outperform Transolver under the same setting on training samples and training epochs as bright blue .

(ii) Accelerating convergence: Under the same training samples, the results surpass the best performance achieved by Transolver trained from scratch, are marked in blue, which indicates the convergence speed, i.e. the smallest epochs to achieve compare performance as training from scratch.

(iii) Reducing data requirements: The results better than Transolver under full training samples and full training epochs are marked in dark blue.

Table 6: Experiments on DrivAerML (Ashton et al., 2024), where we gradually increase the training data from 20 samples to 100 samples and training epochs from 50 epochs to 200 epochs. The relative L2 of Transolver (a) trained from scratch, (b) pre-trained with vector distance supervision, (c) trained with geometry condition, and (d) pre-trained with GeoPT are recorded.

(a) Transolver

Data \ Epoch	50	100	150	200
20	0.374	0.272	0.231	0.206
40	0.328	0.199	0.193	0.140
60	0.215	0.170	0.135	0.112
80	0.206	0.142	0.108	0.102
100	0.197	0.120	0.101	0.093

(b) w/ Geo Pre-train

Data \ Epoch	50	100	150	200
20	0.498	0.525	0.394	0.341
40	0.486	0.424	0.357	0.256
60	0.486	0.320	0.278	0.230
80	0.322	0.271	0.237	0.214
100	0.326	0.251	0.255	0.202

(c) w/ Geo Cond

Data \ Epoch	50	100	150	200
20	0.443	0.362	0.289	0.264
40	0.339	0.264	0.191	0.169
60	0.299	0.175	0.147	0.119
80	0.239	0.159	0.133	0.102
100	0.200	0.133	0.099	0.094

(d) w/ GeoPT

Data \ Epoch	50	100	150	200
20	0.216	0.179	0.160	0.148
40	0.165	0.132	0.121	0.111
60	0.150	0.113	0.100	0.091
80	0.133	0.103	0.089	0.084
100	0.118	0.092	0.080	0.075

Table 7: Experiments on NASA-CRM (Bekemeyer et al., 2025). The relative L2 error under different training data and epochs is recorded.

(a) Transolver

Data \ Epoch	50	100	150	200
21	0.516	0.412	0.351	0.300
42	0.437	0.299	0.225	0.190
63	0.329	0.241	0.168	0.137
84	0.282	0.170	0.123	0.115
105	0.273	0.150	0.112	0.100

(b) w/ Geo Pre-train

Data \ Epoch	50	100	150	200
21	0.435	0.350	0.342	0.290
42	0.397	0.277	0.248	0.194
63	0.286	0.210	0.178	0.163
84	0.276	0.157	0.155	0.116
105	0.237	0.162	0.121	0.099

(c) w/ Geo Cond

Data \ Epoch	50	100	150	200
21	0.458	0.390	0.347	0.321
42	0.394	0.299	0.271	0.230
63	0.343	0.253	0.208	0.188
84	0.319	0.223	0.175	0.139
105	0.277	0.193	0.167	0.112

(d) w/ GeoPT

Data \ Epoch	50	100	150	200
21	0.289	0.268	0.259	0.250
42	0.226	0.187	0.169	0.160
63	0.173	0.127	0.123	0.114
84	0.142	0.108	0.099	0.094
105	0.124	0.099	0.093	0.088

Table 8: AirCraft (2025) results. Relative L2 under different training data and epochs is recorded.

(a) Transolver

Data \ Epoch	50	100	150	200
20	0.586	0.401	0.207	0.172
40	0.319	0.198	0.195	0.138
60	0.226	0.247	0.138	0.122
80	0.197	0.175	0.158	0.138
100	0.153	0.136	0.137	0.110

(b) w/ Geo Pre-train

Data \ Epoch	50	100	150	200
20	0.595	0.486	0.365	0.247
40	0.562	0.321	0.296	0.237
60	0.519	0.304	0.317	0.213
80	0.360	0.199	0.189	0.191
100	0.199	0.165	0.170	0.199

(c) w/ Geo Cond

Data \ Epoch	50	100	150	200
20	0.567	0.266	0.211	0.186
40	0.317	0.218	0.191	0.142
60	0.299	0.234	0.163	0.124
80	0.259	0.214	0.153	0.125
100	0.238	0.195	0.161	0.118

(d) w/ GeoPT

Data \ Epoch	50	100	150	200
20	0.567	0.264	0.197	0.170
40	0.240	0.159	0.147	0.122
60	0.224	0.159	0.121	0.107
80	0.151	0.135	0.113	0.103
100	0.134	0.117	0.101	0.090

Table 9: DTCHull results. The relative L2 error under different training data and epochs is recorded.

(a) Transolver

Data \ Epoch	50	100	150	200
20	0.525	0.444	0.404	0.388
40	0.381	0.303	0.228	0.230
60	0.343	0.226	0.209	0.190
80	0.286	0.210	0.198	0.186
100	0.240	0.211	0.198	0.181

(b) w/ Geo Pre-train

Data \ Epoch	50	100	150	200
20	0.504	0.464	0.373	0.426
40	0.411	0.349	0.242	0.276
60	0.339	0.333	0.211	0.223
80	0.330	0.269	0.231	0.200
100	0.304	0.219	0.225	0.190

(c) w/ Geo Cond

Data \ Epoch	50	100	150	200
20	0.433	0.435	0.426	0.404
40	0.359	0.359	0.337	0.330
60	0.325	0.294	0.304	0.271
80	0.303	0.278	0.250	0.242
100	0.284	0.254	0.247	0.211

(d) w/ GeoPT

Data \ Epoch	50	100	150	200
20	0.294	0.258	0.229	0.229
40	0.196	0.182	0.177	0.180
60	0.164	0.158	0.163	0.160
80	0.159	0.154	0.152	0.155
100	0.149	0.149	0.146	0.146

Table 10: Car-Crash results. The relative L2 error under different training data and epochs is recorded.

(a) Transolver

Data \ Epoch	50	100	150	200
20	0.490	0.440	0.384	0.364
40	0.438	0.358	0.318	0.282
60	0.389	0.319	0.274	0.217
80	0.357	0.288	0.231	0.202
100	0.337	0.254	0.205	0.198

(b) w/ Geo Pre-train

Data \ Epoch	50	100	150	200
20	0.386	0.332	0.306	0.294
40	0.398	0.354	0.306	0.296
60	0.370	0.307	0.280	0.273
80	0.338	0.301	0.269	0.244
100	0.318	0.268	0.248	0.225

(c) w/ Geo Cond

Data \ Epoch	50	100	150	200
20	0.474	0.421	0.391	0.365
40	0.421	0.361	0.328	0.298
60	0.395	0.330	0.293	0.256
80	0.368	0.315	0.255	0.233
100	0.345	0.274	0.238	0.193

(d) w/ GeoPT

Data \ Epoch	50	100	150	200
20	0.356	0.311	0.278	0.260
40	0.296	0.263	0.232	0.219
60	0.268	0.237	0.209	0.194
80	0.252	0.211	0.194	0.185
100	0.236	0.198	0.184	0.177

Statistical test In Table 11, we also include the standard deviation of key results under 5 runs for statistical analysis. Under the statistical test, all training-data-saving claims are supported by 95% confidence intervals, where the equivalence margin is set as 0.001.

Table 11: Standard deviation of relative L2 under 5 runs.

Standard deviation ($\times 10^{-3}$)	DrivAerML	NASA-CRM	AirCraft	DTCHull	Car-Crash
From Scratch 100% Training data	0.43	0.94	1.03	1.34	0.71
GeoPT 100% Training data	0.68	0.35	1.23	0.88	0.31
GeoPT 80% Training data	0.80	0.66	1.27	1.10	0.56
GeoPT 60% Training data	0.81	0.93	1.17	0.49	0.13
GeoPT 40% Training data	0.31	0.76	1.83	0.91	0.76

Representation visualization Due to space limitations in the main text, we present the complete visualization of the physics states in Fig. 21-24 as a supplement to Fig. 3 and 7, which includes the learned correlations under various supervisions and dynamics-dependent correlations prompted by different configurations of dynamics conditions.

G Limitations and Future Work

This paper provides a scalable pathway to utilize off-the-shelf geometries for pre-training neural simulators and has demonstrated effectiveness in extensive industrial-fidelity simulations. Despite favorable performance and generalizability, GeoPT also has some limitations in the following aspects.

In GeoPT, we propose to parameterize the diverse simulation settings into a point-wise dynamics field, which can cover the diversity in geometry, flow direction and speed, as well as material differences of typical simulation benchmarks. Although this is one step forward in unifying diverse simulation tasks but still cannot precisely describe all kinds of settings. For example, in the crash simulation that considers both elastic and strength properties of materials, the most reasonable to parameterize two properties into one dynamic speed value for every element, while this may lose some distinguishability due to the dimension reduction. However, since we only focus on the pre-training process, such a limitation can be resolved by extending the input channel and tuning new parameters with zero initialization, like ControlNet (Zhang et al., 2023). In the future, we would like to explore a more general framework to unify diverse simulation tasks.

GeoPT primarily targets simulations involving complex geometries, a common requirement in industrial design and a setting where neural simulators have achieved their most notable successes. Additionally, it is also interesting to see the extension of GeoPT to simulations without complex geometry boundaries, such as 3D turbulence in regular grids (Perlman et al., 2007). Since such simulations are mainly about computationally intensive physics interactions, the previous explorations (Holzschuh et al., 2025) still rely on expensive physics supervision. Taking such regular grid simulation into account, one possible way is to leave a certain ratio of pre-training iterations for dynamics under an empty geometry boundary during the pre-training process of GeoPT, where all the tracking points are in free-flight motion, which can make the model learn the intrinsic isotropic dynamics. We would like to leave this exploration as future work.

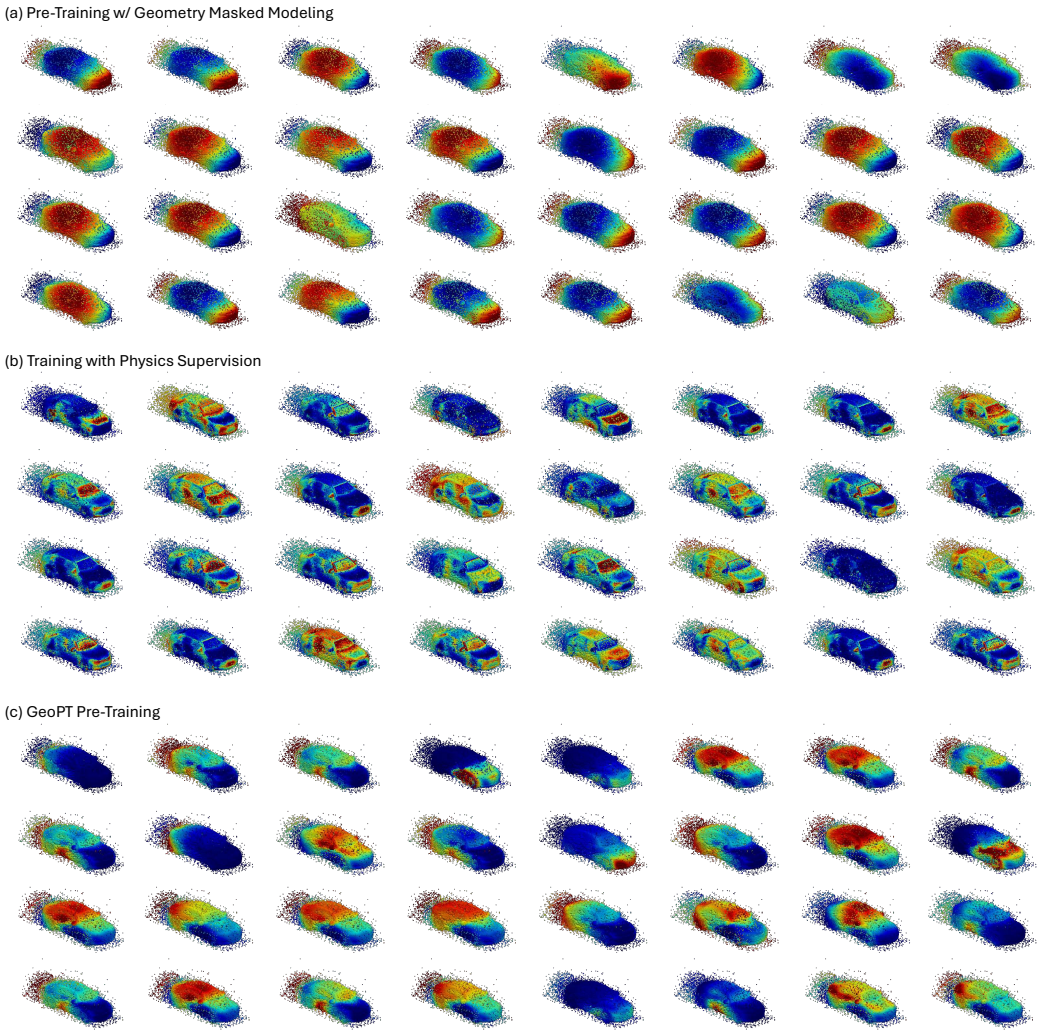


Figure 21: Visualization of physical states learned from different supervision signals, including (a) pre-training by learning to predict vector distance, (b) directly training with DrivAerML physics supervision and (c) pre-training with the dynamic process proposed by GeoPT. Here, we visualize the last layer. Other layer visualizations can differ in absolute value but share a similar distribution.

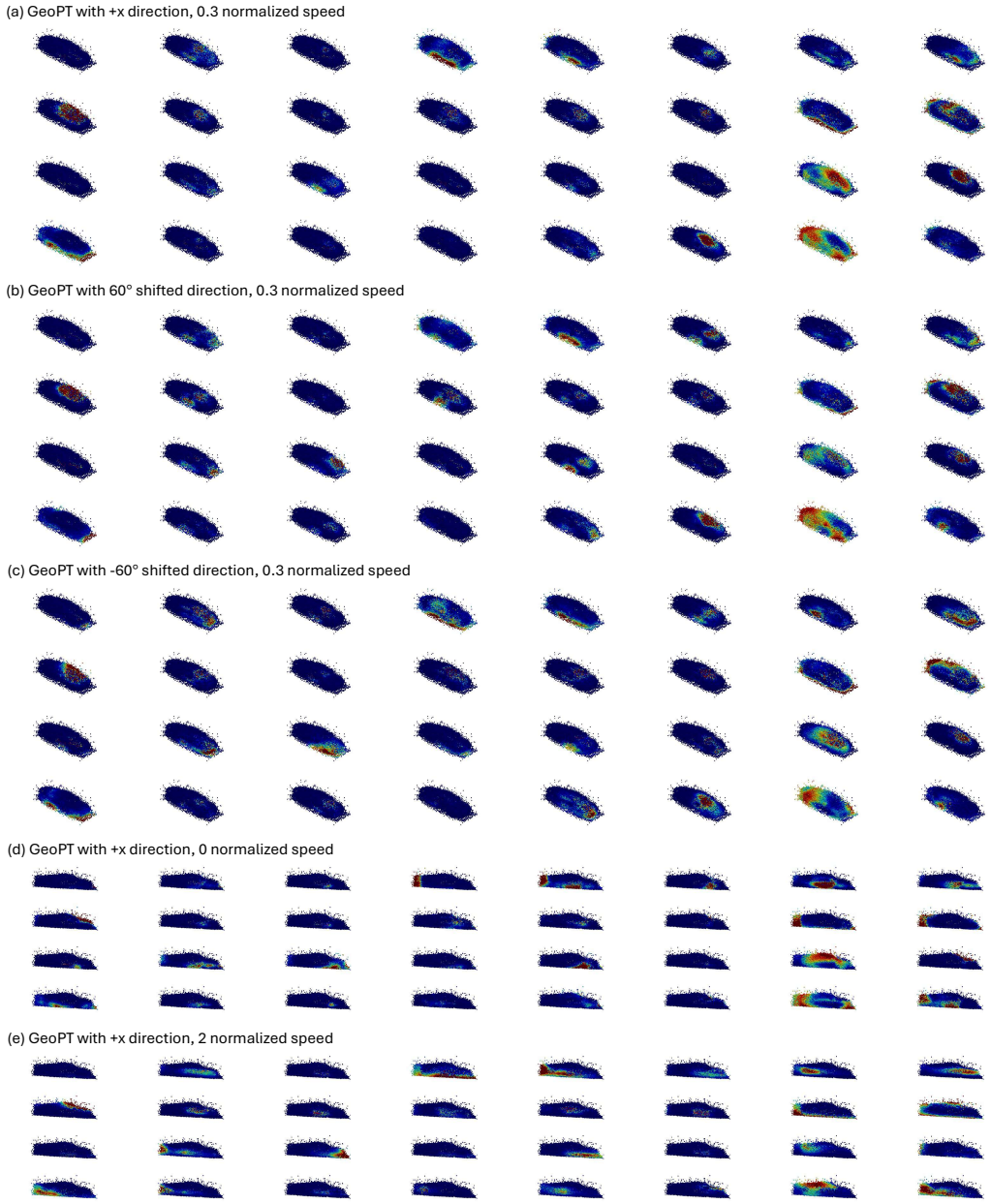


Figure 22: Visualization of DrivAerML physical states in GeoPT "prompted" from different dynamics configurations, including varied (a-c) direction and (d-e) velocity norm (speed) configurations. Here, we visualize the fourth layer as a supplement to the last layer visualization in Fig. 21. Notably, the states in the fourth layer are less distinguishable in the middle layers when compared with the last layer. This can be viewed as an architectural feature of Transolver, which can enable better global interaction among different states.

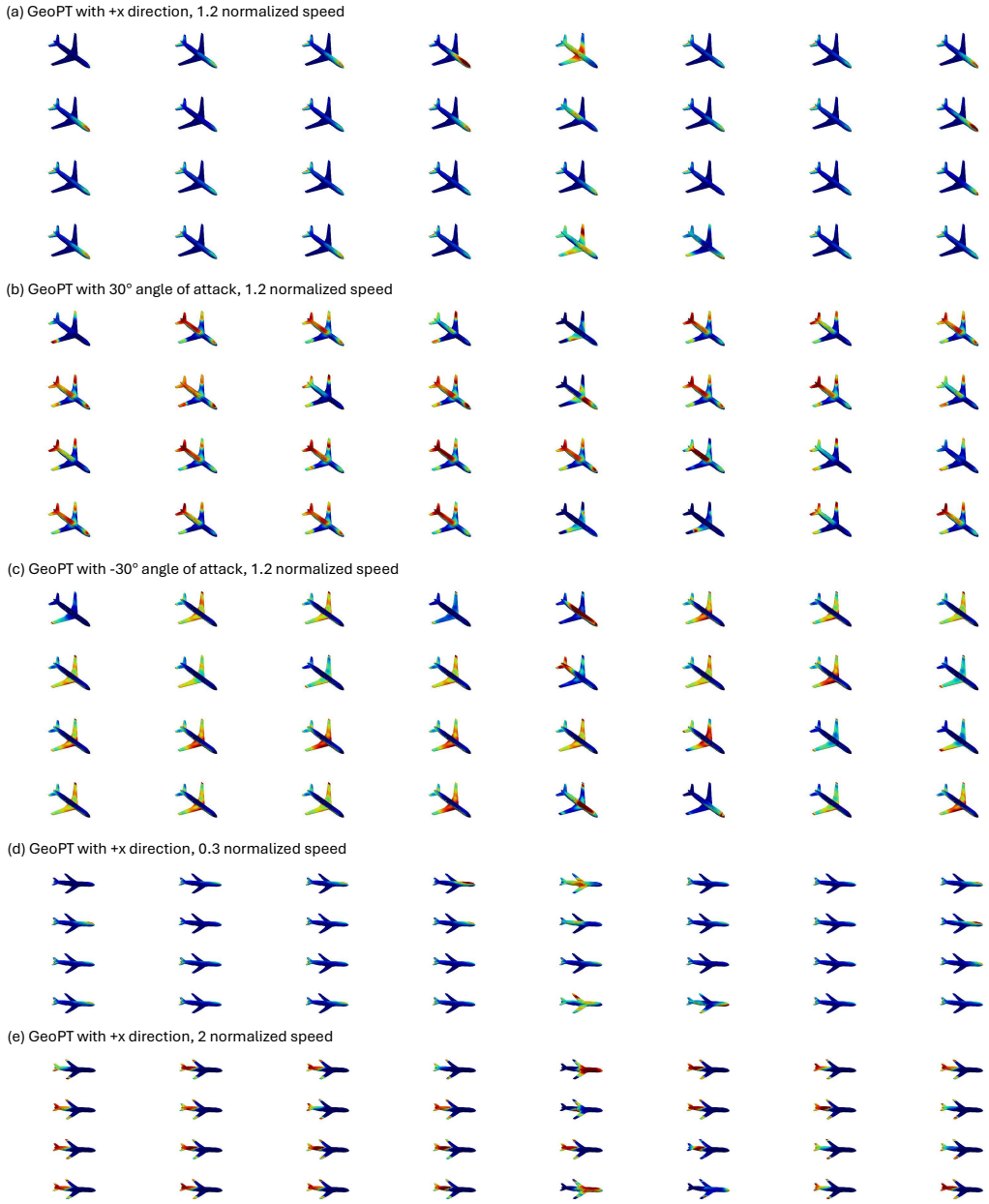


Figure 23: Visualization of NASA-CRM physical states in GeoPT "prompted" from different dynamics configurations, including varied (a-c) direction and (d-e) speed configurations. Here, we visualize the physical states in the last layer. Similar to DrivAerML, changing the angle of attack in the y-z plane will affect the state distribution and increasing speed will lead to a more concentrated state distribution.

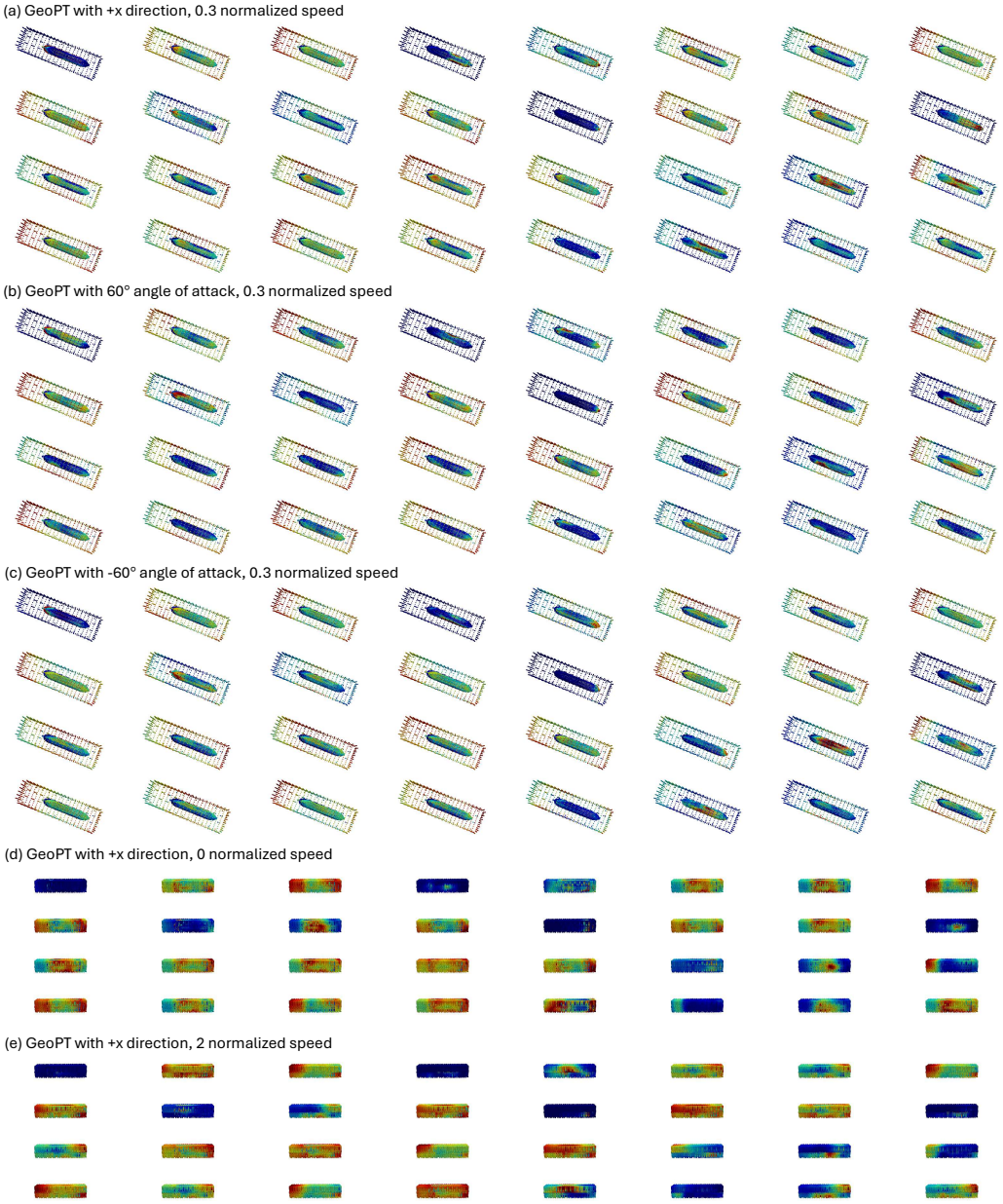


Figure 24: Visualization of DTCHull physical states in GeoPT "prompted" from different dynamics configurations, including varied (a-c) direction and (d-e) speed configurations. Here, we visualize the physical states in the last layer. Notably, to ensure a clear presentation of the inside ship surface, we downsample the mesh by 10 times for visualization.