

the PDEs rather than

relying on superficial shortcut features.

fail to learn true physical features instead it recursively replicates prior predictions.

# Physics-informed Temporal Alignment for Auto-regressive PDE Foundation Models

Congcong Zhu\* Xiaoyan Xu\* Jiayue Han Jingrun Chen \* indicates equal contribution



2025

## **Background & Motivation**

Auto-regressive foundation models for partial differential equations (PDEs) have shown promise over traditional methods:

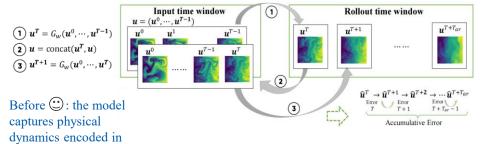
> **Higher Generalization Capacity Lower Computational Costs Towards General Scientific Intelligence**

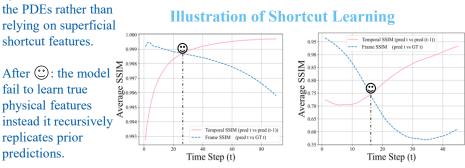
It takes  $T_{in}$  frames as input and predict the next frames based on previous ones

$$\widehat{\boldsymbol{u}}_{t+1} = G_{\boldsymbol{\theta}}(\{\boldsymbol{u}_i\}_{i=t-T_{in}+1}^t)$$

But it suffers from error accumulation over long rollout horizons due to shortcut learning phenomena.

## **Illustration of Error Accumulation**



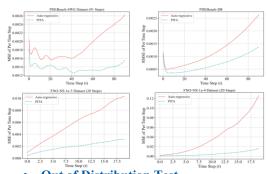


#### 2. Data-driven PDE 1. Auto-regressive **Methodology** discovery and Tem-Prediction. The model poral alignment is takes initial states 1. Auto-regressive Prediction 2. Data-Driven Governing Equations Discovery then performed on $\{\boldsymbol{u}_t\}_{t=1}^{T_{in}}$ as input and the input sequence $\partial_t \boldsymbol{U}(\boldsymbol{\theta}) = \boldsymbol{\Phi}(\boldsymbol{\theta}) \boldsymbol{\Lambda}$ predict future states to infer the $\{\widehat{\boldsymbol{u}}_t\}_{t=T_{in}+1}^{T_{in}+T_{ar}}$ governing PDEs. Sparse Regression Consistency Nonlinear Library of Data and Derivatives Supervision Back-Propagation Auto-regressive PDE Identified Compressed **Foundation Model** Physics Supervision $D\partial_t \boldsymbol{U}(\boldsymbol{\theta}) = D \boldsymbol{\Phi}(\boldsymbol{\theta}) \boldsymbol{\Lambda}$ 3. Alternating Optimization Down-Uncertainty-Based Weights Compressed sample Sparse Regression Data Supervision 3. An uncertainty-Compressed Library based strategy is employed to adjust the weights between **Experiments** $L_{Data}$ , $L_{Phy}$ and $L_{Con}$

### **In Distribution Test**

					-50										
	Finetune	ne FNO-NS-ν			PDEBench		PDEBench-CNS- $(M, \eta)$						PDEArena		CFDBench
Model	Strategy	1e-5	1e-4	1e-3	DR	SWE	1,0.1	1,0.01	M1	0.1,0.1	0.1,0.01	M0.1	NS-Force	NS	-
							Predict shor	t trajectory							
DPOT-Ti	Auto-regress	0.05200	0.00385	0.00380	0.01326	0.00208	0.01120	0.01950	0.01535	0.01740	0.01380	0.01560	0.10269	0.09100	0.00391
7M	PITA	0.05629	0.00499	0.00218	0.02119	0.00202	0.01793	0.01565	0.01679	0.01080	0.01250	0.01165	0.11988	0.06465	0.00360
DPOT-S	Auto-regress	0.03220	0.00641	0.00301	0.01239	0.00210	0.01290	0.01670	0.01480	0.0152	0.01260	0.01390	0.07598	0.08670	0.00382
30M	PITA	0.02240	0.00232	0.00157	0.01346	0.00150	0.01057	0.01217	0.01137	0.01750	0.01140	0.01445	0.06769	0.04190	0.00335
MPP-Ti	Auto-regress	-	-	-	0.03510	0.00645	-	-	0.05841	-	-	0.04611	-	-	-
7M	PITA	-	-	-	0.03384	0.00605	-	-	0.04370	-	-	0.04025	-	-	-
MPP-S	Auto-regress	-	-	-	0.02974	0.00281	-	-	0.04287	-	-	0.02012	-	-	-
30M	PITA	-	-	-	0.03024	0.00274	-	-	0.04051	-	-	0.01906	-	-	-
DPOT-M	Auto-regress	0.02290	0.00385	0.00297	0.01209	0.00219	0.00998	0.01460	0.01230	0.01610	0.00947	0.01280	0.05571	0.02940	0.00373
122M	PITA	0.03199	0.00185	0.00193	0.00957	0.00154	0.01101	0.01032	0.01067	0.00945	0.01010	0.00958	0.05829	0.02191	0.00289
FNO-M	Auto-regress	0.08036	0.00577	0.00302	0.08608	0.00501	0.27849	0.03345	0.15597	0.13200	0.04449	0.08825	0.15190	0.15590	0.01382
170M	PITA	0.07668	0.00552	0.00152	0.07014	0.00423	0.10947	0.03483	0.07215	0.10224	0.05686	0.07955	0.15594	0.14066	0.00756
DPOT-L	Auto-regress	0.02130	0.00400	0.00298	0.00801	0.00184	0.01080	0.01310	0.01195	0.01600	0.00905	0.01253	0.05493	0.02780	0.00322
500M	PITA	0.01059	0.00198	0.00139	0.01084	0.00172	0.01001	0.00995	0.00998	0.02004	0.01871	0.01938	0.04965	0.02048	0.00302
							Predict long	trajectory							
DPOT-Ti	Auto-regress		0.03670	0.00580	0.01480	0.00241	-						0.30034	-	-
7M	PITA	-	0.01718	0.00327	0.01090	0.00199	-	-	-	-	-	-	0.31012	-	-
DPOT-S	Auto-regress	-	0.02370	0.00437	0.01350	0.00235	-	-	-	-	-	-	0.26800	-	-
30M	PITA		0.00854	0.00223	0.00994	0.00137	-	-		-	-		0.22620	-	-
MPP-Ti	Auto-regress	-	-	-	0.05212	0.03291	-	-	-	-	-	-	-	-	-
7M	PITA	-	-	-	0.03844	0.02174	-	-	-	-	-	-	-	-	-
MPP-S	Auto-regress	-	-	-	0.04258	0.01631	-	-	-	-	-	-	-	-	-
30M	PITA	-	-	-	0.03704	0.00950	-	-	-	-	-	-	-	-	-
DPOT-M	Auto-regress		0.0126	0.00335	0.01030	0.00227	-	-		-	-		0.17200	-	-
122M	PITA		0.00694	0.00139	0.00904	0.00135	-	-		-	-	-	0.16390	-	-
FNO-M	Auto-regress	-	0.01761	0.00425	0.04101	0.00924	-	-	-	-	-	-	0.43136	-	-
170M	PITA	-	0.01710	0.00227	0.02884	0.00614	-	-	-	-	-	-	0.38731	-	-
DPOT-L	Auto-regress	-	0.0104	0.00323	0.00739	0.00170	-	-	-	-	-	-	0.17000	-	-

## **Performance on Shortcut Issue Resolution**



## Out of Distribution Test

Model		PI	DEArena-SV	Burgers						
	Strategy	500	1000	1500	500	1000	1500			
DPOT-Ti	Finetune (Auto-regress)	18.46497	5.24994	1.01142	0.03712	0.02543	0.00455			
	Train from Scratch (Auto-regress)	5.98731	3.20792	0.99990	0.06691	0.01526	0.00419			
	Train from Scratch (PITA)	2.07097	3.89625	0.99710	0.06945	0.01318	0.00374			
	Finetune (Auto-regress)	44.70683	2.69744	0.99152	0.04679	0.01627	0.00304			
DPOT-S	Train from Scratch (Auto-regress)	8.00870	2.66849	0.99414	0.06251	0.02703	0.00383			
	Train from Scratch (PITA)	16.16088	1.87741	0.99051	0.04121	0.01943	0.00307			