Novelty Assessment Report

Paper: Fast training of accurate physics-informed neural networks without gradient descent
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Abstract

Solving time-dependent Partial Differential Equations (PDEs) is one of the most critical problems in computational science. While Physics-Informed Neural Networks (PINNs) offer a promising framework for approximating PDE solutions, their accuracy and training speed are limited by two core barriers: gradient-descent-based iterative optimization over complex loss landscapes and non-causal treatment of time as an extra spatial dimension. We present Frozen-PINN, a novel PINN based on the principle of space-time separation that leverages random features instead of training with gradient descent, and incorporates temporal causality by construction. On nine PDE benchmarks, including challenges like extreme advection speeds, shocks, and high-dimensionality, Frozen-PINNs achieve superior training efficiency and accuracy over state-of-the-art PINNs, often by several orders of magnitude. Our work addresses longstanding training and accuracy bottlenecks of PINNs, delivering quickly trainable, highly accurate, and inherently causal PDE solvers, a combination that prior methods could not realize. Our approach challenges the reliance of PINNs on stochastic gradient-descent-based methods and specialized hardware, leading to a paradigm shift in PINN training and providing a challenging benchmark for the community.

Core Task Landscape

This paper addresses: **Solving Time-Dependent Partial Differential Equations Using Neural Networks**

A total of **50 papers** were analyzed and organized into a taxonomy with **25 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Physics-Informed Neural Network Architectures and Training Methods**
- **Data-Driven and Operator Learning Methods**
- **PDE Discovery and System Identification**
- **Specialized PDE Classes and Problem Formulations**
- **Numerical Stability and Long-Term Prediction**
- **Hybrid and Differentiable Numerical Solvers**
- **Sampling and Generative Modeling via PDE Transport**
- **General Neural Network Frameworks for Time-Varying Systems**
- **Zeroing Neural Networks for Time-Varying Equations**
- **Domain-Specific Applications**

Complete Taxonomy Tree

- Solving Time-Dependent Partial Differential Equations Using Neural Networks Survey Taxonomy
- Physics-Informed Neural Network Architectures and Training Methods
  - Causality-Aware and Temporal Structure Exploitation ★ (4 papers)
  - [0] Fast training of accurate physics-informed neural networks without gradient descent (Anon et al., 2026) View paper
  - [1] Solving partial differential equations with sampled neural networks (Datar, 2024) View paper
  - [3] Real-time full-field estimation of transient responses in time-dependent partial differential equations using causal physics-informed neural networks with sparse â¦ (HK Noh, 2025) View paper
  - [43] Causality-enhanced Discreted Physics-informed Neural Networks for Predicting Evolutionary Equations (Thomas Eiter, 2024) View paper
  - Recurrent and Sequential PINN Formulations (2 papers)
  - [17] A physics-informed recurrent neural network for solving time-dependent partial differential equations (Ying Liang, 2024) View paper
  - [33] Dual-level time-marching neural network for solving time-dependent partial differential equations: J. Guo et al. (J Guo, 2025) View paper
  - Hybrid Finite Element and PINN Methods (1 papers)
  - [15] A hybrid FEM-PINN method for time-dependent partial differential equations (Feng Xiao-dong, 2024) View paper
  - Domain Decomposition and Multi-Scale PINN Strategies (3 papers)
  - [10] Sinenet: Learning temporal dynamics in time-dependent partial differential equations (Zhang Xuan, 2024) View paper
  - [24] â¦ -informed neural networks (XPINNs): A generalized space-time domain decomposition based deep learning framework for nonlinear partial differential equations (AD Jagtap, 2020) View paper
  - [31] Multi-resolution partial differential equations preserved learning framework for spatiotemporal dynamics (Xinâ Yang Liu, 2024) View paper
  - Stochastic and Uncertainty-Aware PINN Extensions (2 papers)
  - [6] Learning in modal space: Solving time-dependent stochastic PDEs using physics-informed neural networks (Dongkun Zhang, 2020) View paper

  - [29] DR-PDE-Net: A time-varying inverse multi-physics-informed neural network paradigm for solving dimension-reduced probability density evolution equation in noisy â€¦ (TT Hao, 2025) View paper
  - Preconditioning and Optimization Enhancements for PINNs (2 papers)
  - [27] A pseudo-time stepping and parameterized physics-informed neural network framework for Navierâ€“Stokes equations (Zhuo Zhang, 2025) View paper
  - [46] Solving partial differential equations based on preconditioning-pretraining physics-informed neural network (Zihan Wang, 2025) View paper
  - Convolutional and Spatially-Constrained PINNs (3 papers)
  - [35] Transfer learning-based physics-informed convolutional neural network for simulating flow in porous media with time-varying controls (Jungang Chen, 2024) View paper
  - [41] Physics-constrained convolutional neural networks for inverse problems in spatiotemporal partial differential equations (Daniel Kelshaw, 2024) View paper
  - [44] Solving spatial-temporal PDEs with arbitrary boundary conditions using physics-constrained convolutional recurrent neural networks (Guangfa Li, 2025) View paper
  - Geometry-Aware and Graph-Based PINNs (1 papers)
  - [47] Physics-and geometry-aware spatio-spectral graph neural operator for time-independent and time-dependent PDEs (Chakraborty, 2025) View paper
- Data-Driven and Operator Learning Methods
  - Neural Operator Frameworks (4 papers)
  - [2] GraphDeepONet: Learning to simulate time-dependent partial differential equations using graph neural network and deep operator network (SW Cho, 2024) View paper
  - [7] Machine-learning-based spectral methods for partial differential equations (B. Meuris, 2023) View paper
  - [23] Vectorized conditional neural fields: A framework for solving time-dependent parametric partial differential equations (Kalimuthu Marimuthu, 2024) View paper
  - [32] Towards multi-spatiotemporal-scale generalized pde modeling (Gupta, 2022) View paper
  - Graph Neural Network Simulators (2 papers)
  - [25] Data-Efficient Time-Dependent PDE Surrogates: Graph Neural Simulators vs. Neural Operators (Nayak, 2025) View paper
  - [39] Solving Nonlinear Conservation Laws of Partial Differential Equations Using Graph Neural Networks (Qing Li, 2023) View paper
  - Sequence-to-Sequence and Recurrent Architectures (2 papers)
  - [4] Neural time-dependent partial differential equation (Yihao Hu, 2021) View paper
  - [40] Egpde-net: building continuous neural networks for time series prediction with exogenous variables (Penglei Gao, 2024) View paper
  - Latent Space and Reduced Order Modeling (2 papers)
  - [14] Learning to accelerate partial differential equations via latent global evolution (Wu, 2022) View paper
  - [21] A comprehensive deep learning-based approach to reduced order modeling of nonlinear time-dependent parametrized PDEs (Fresca, 2021) View paper
  - Evolutional and Parameter-Space Neural Networks (2 papers)
  - [19] Neural control of parametric solutions for high-dimensional evolution pdes (Nathan Gaby, 2024) View paper
  - [30] Evolutional deep neural network (Du, 2021) View paper
  - Hypernetwork and Multi-Expert Architectures (2 papers)
  - [26] MM: Learning controllable Multi of experts and multi-scale operators are the Partial Differential Equations need (A Liang, 2024) View paper
  - [28] DISCO: learning to DISCover an evolution Operator for multi-physics-agnostic prediction (Morel, 2025) View paper
- PDE Discovery and System Identification (4 papers)
  - [12] Deep-learning of parametric partial differential equations from sparse and noisy data (Hao Xu, 2021) View paper
  - [20] NeuPDE: Neural network based ordinary and partial differential equations for modeling time-dependent data (Sun, 2020) View paper
  - [22] Deep hidden physics models: Deep learning of nonlinear partial differential equations (Raissi, 2018) View paper
  - [45] From disorganized data to emergent dynamic models: Questionnaires to partial differential equations (David W Sroczynski, 2025) View paper
- Specialized PDE Classes and Problem Formulations
  - Fractional and Integro-Differential Equations (1 papers)
  - [11] Solving Time-Fractional Partial Integro-Differential Equations Using Tensor Neural Network (Zhongshuo Lin, 2025) View paper
  - Nonlinear Conservation Laws and Shock Phenomena (1 papers)
  - [8] Solving second-order nonlinear evolution partial differential equations using deep learning (Jun Li, 2020) View paper
  - PDE-Constrained Optimization and Inverse Problems (1 papers)
  - [49] Learning to Solve Optimization Problems Constrained with Partial Differential Equations (Di Vito, 2025) View paper
  - Parametric PDEs and Generalization Across Conditions (2 papers)
  - [34] Solving initial-boundary value problems for systems of partial differential equations using neural networks and optimization techniques (R. S. Beidokhti, 2009) View paper
  - [37] Neural oscillators for generalizing parametric PDEs (T Kapoor, 2023) View paper
- Numerical Stability and Long-Term Prediction (2 papers)
  - [36] Implicit Neural Differential Model for Spatiotemporal Dynamics (Deepak Akhare, 2025) View paper
  - [38] Pde-refiner: Achieving accurate long rollouts with neural pde solvers (Lippe, 2023) View paper
- Hybrid and Differentiable Numerical Solvers (1 papers)
  - [42] Numerical PDE solvers outperform neural PDE solvers (Patrick Chatain, 2025) View paper
- Sampling and Generative Modeling via PDE Transport (1 papers)
  - [48] Dynamical measure transport and neural PDE solvers for sampling (Sun, 2024) View paper
- General Neural Network Frameworks for Time-Varying Systems (2 papers)
  - [5] Deep learning methods for modeling of spatiotemporal dynamical systems governed by partial differential equations (Iakovlev, 2025) View paper
  - [13] Dynamic neural network models for time-varying problem solving: A survey on model structures (Cheng Hua, 2023) View paper

- Zeroing Neural Networks for Time-Varying Equations (3 papers)
  - [9] Prescribed-time delayed zeroing neural network for solving time-varying equations and its applications (Dongmei Yu, 2025) View paper
  - [16] An efficient zeroing neural network for solving time-varying nonlinear equations (Ratikanta Behera, 2023) View paper
  - [18] Zhang neural networks: an introduction to predictive computations for discretized time-varying matrix problems (Frank Uhlig, 2024) View paper
- Domain-Specific Applications (1 papers)
  - [50] Neural Network Architectures for Simulating Time-Varying Room Acoustics (Hannah Cho, 2024) View paper

Narrative

Core task: Solving time-dependent partial differential equations using neural networks. The field has evolved into a rich ecosystem of approaches that can be broadly organized into several major branches. Physics-Informed Neural Network (PINN) architectures and training methods focus on embedding governing equations directly into loss functions, often exploring causality-aware structures and temporal exploitation strategies to improve accuracy and efficiency. Data-driven and operator learning methods, exemplified by works like GraphDeepONet[2], learn solution operators from observations rather than relying solely on equation residuals. PDE discovery and system identification aim to infer unknown governing equations from data, while specialized formulations target particular equation classes such as conservation laws or reaction-diffusion systems. Numerical stability and long-term prediction address the challenge of error accumulation over extended time horizons, and hybrid approaches combine classical numerical solvers with neural components to leverage the strengths of both paradigms. Additional branches cover sampling and generative modeling via PDE transport, general frameworks for time-varying systems, zeroing neural networks for time-varying equations, and domain-specific applications ranging from fluid dynamics to room acoustics.

Within the causality-aware and temporal structure exploitation line of work, researchers have pursued various strategies to respect the directional flow of time and improve training efficiency. Causal PINN Estimation[3] and Causality Enhanced Discreted[43] both emphasize enforcing temporal causality to prevent information leakage and enhance solution quality, while Sampled Neural Networks[1] explores efficient sampling strategies during training. Fast PINN Training[0] sits naturally within this cluster, focusing on accelerating the training process by exploiting temporal structure, a concern shared by many PINN practitioners who face high computational costs. Compared to Causal PINN Estimation[3], which prioritizes causality constraints, Fast PINN Training[0] appears to emphasize computational efficiency as a primary goal. Meanwhile, broader efforts in the field such as Spatiotemporal Deep Learning[5] and Neural Time PDE[4] tackle related challenges of capturing complex spatiotemporal dependencies, illustrating the diverse strategies researchers employ to make neural PDE solvers both accurate and practical for real-world time-dependent problems.

Related Works in Same Category

The following **3 sibling papers** share the same taxonomy leaf node with the original paper:

1. Solving partial differential equations with sampled neural networks

Authors: Datar, Chinmay, Kapoor, Taniya, Chinmay Datar, et al. (25 authors total) | **Year/Venue**: 2024 | **URL**: View paper

Abstract

Solving time-dependent Partial Differential Equations (PDEs) is one of the most critical problems in computational science. While Physics-Informed Neural Networks (PINNs) offer a promising framework for approximating PDE solutions, their accuracy and training speed are limited by two core barriers: gradient-descent-based iterative optimization over complex loss landscapes and non-causal treatment of time as an extra spatial dimension. We present Frozen-PINN, a novel PINN based on the principle o...

⚠ Similarity Notice

This paper appears to be highly similar to the original paper, with nearly identical abstracts describing the same Frozen-PINN method, space-time separation principle, random features approach, and benchmark results. The only notable difference is the number of benchmarks mentioned (eight vs. nine), suggesting this may be a variant submission or earlier/later version of the same work.

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2. Real-time full-field estimation of transient responses in time-dependent partial differential equations using causal physics-informed neural networks with sparse â¦

Authors: HK Noh, M Choi, JH Lim | **Year/Venue**: 2025 | **URL**: View paper

Abstract

Real-time full-field estimation of transient responses in time-dependent partial differential equations using causal physics-informed neural networks with sparse measurements - â¦

Relationship Analysis

Both papers belong to the causality-aware and temporal structure exploitation category, addressing temporal causality in physics-informed neural networks for time-dependent PDEs. The candidate paper focuses on real-time full-field estimation using sparse measurements with causal PINNs, emphasizing data assimilation and sensor-based reconstruction, while the original paper (Frozen-PINN) addresses causality through space-time separation with frozen random features and gradient-descent-free training via ODE solvers. The key distinction is that the candidate targets inverse/estimation problems with measurement data, whereas Frozen-PINN focuses on forward PDE solving without requiring observational data.

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3. Causality-enhanced Discreted Physics-informed Neural Networks for Predicting Evolutionary Equations

Authors: Thomas Eiter, Tobias Geibinger, Ye Li, Siqi Chen, Bin Shan, et al. (6 authors total) | **Year/Venue**: 2024 • International Joint Conference on Artificial Intelligence | **URL**: View paper

Abstract

Physics-informed neural networks (PINNs) have shown promising potential for solving partial differential equations (PDEs) using deep learning.

However, PINNs face training difficulties for evolutionary PDEs, particularly for dynamical systems whose solutions exhibit multi-scale or turbulent behavior over time.

The reason is that PINNs may violate the temporal causality property since all the temporal features in the PINNs loss are trained simultaneously.

This paper proposes to use implicit ...

Relationship Analysis

Both papers belong to the Causality-Aware and Temporal Structure Exploitation category, addressing the fundamental challenge of enforcing temporal causality in PINNs for time-dependent PDEs. The candidate paper enforces causality through implicit time differencing schemes with transfer learning to sequentially update PINNs across time frames, while the original paper achieves causality through space-time separation with frozen spatial bases and ODE solvers for temporal evolution. The key difference is that the original paper eliminates gradient descent entirely using random features and reformulates the problem as an ODE, whereas the candidate paper still relies on gradient-based training but applies it sequentially across time windows.

Contributions Analysis

Overall novelty summary. The paper introduces Frozen-PINN, a method combining space-time separation with random features and temporal causality for solving time-dependent PDEs. It resides in the 'Causality-Aware and Temporal Structure Exploitation' leaf, which contains only four papers total, indicating a relatively sparse research direction within the broader PINN landscape. This leaf sits under 'Physics-Informed Neural Network Architectures and Training Methods', one of the major branches in a taxonomy spanning 50 papers across diverse approaches. The small sibling set suggests this specific combination of causality enforcement and training efficiency remains an active but not yet crowded area.

The taxonomy reveals neighboring leaves addressing related but distinct concerns: 'Recurrent and Sequential PINN Formulations' (2 papers) explores temporal continuity through recurrent architectures, while 'Domain Decomposition and Multi-Scale PINN Strategies' (3 papers) tackles spatiotemporal complexity through partitioning rather than causality. 'Preconditioning and Optimization Enhancements for PINNs' (2 papers) shares the efficiency motivation but focuses on gradient-based optimization improvements. The taxonomy's scope note for the target leaf explicitly excludes methods treating time as a standard spatial dimension, positioning Frozen-PINN's causal approach as a deliberate departure from conventional PINN formulations that dominate other branches.

Among 25 candidates examined, the Frozen-PINN training algorithm (Contribution 1) shows one refutable candidate from 5 examined, while adaptive solution-driven parameters (Contribution 2) also has one refutable candidate from 10 examined. The SVD compression layer (Contribution 3) found no refutable prior work among 10 candidates. These statistics reflect a limited search scope rather than exhaustive coverage: the analysis captures top-K semantic matches and citation expansion, not the entire literature. The training algorithm and adaptive parameters appear to have some precedent in the examined subset, while the compression approach shows less overlap within this sample.

Given the sparse taxonomy leaf and limited search scope, the work appears to occupy a relatively underexplored intersection of causality enforcement and training efficiency. The two refutable pairs among 25 candidates suggest partial overlap with prior efforts, but the small sibling set (4 papers) and narrow search window mean substantial related work may exist outside the examined sample. The assessment reflects what 25 semantically similar papers reveal, not a definitive novelty verdict across all PINN literature.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Frozen-PINN training algorithm

Description: The authors introduce Frozen-PINN, a novel physics-informed neural network that uses space-time separation, random features instead of gradient descent, and incorporates temporal causality by construction. This approach achieves superior training efficiency and accuracy compared to existing PINNs.

This contribution was assessed against **5 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. Statistical and Machine Learning Methods for Physics-Informed Spatiotemporal Models With Applications to Wildlife Diseases

URL: View paper

Brief Assessment

Wildlife Disease Spatiotemporal[71] focuses on statistical and machine learning methods for wildlife disease modeling, not physics-informed neural networks or PDE solvers. The candidate addresses entirely different application domains and methodologies.

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2. Multiscale Physics-Informed Neural Network Framework to Capture Stochastic Thin-Film Deposition

URL: View paper

Brief Assessment

Stochastic Thin Film[70] focuses on multiscale stochastic PDEs for thin-film deposition using standard PINN training with embedded loss functions, not on space-time separation with random features and gradient-descent-free training.

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3. Physics-aware Causal Graph Network for Spatiotemporal Modeling

URL: View paper

Brief Assessment

Causal Graph Network[69] focuses on spatiotemporal causal structure learning for forecasting tasks, not on physics-informed neural network training algorithms or space-time separation methods for solving PDEs.

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4. Solving partial differential equations with sampled neural networks

URL: View paper

Prior Art Analysis

Sampled Neural Networks[1] demonstrates that the core technical approach of Frozen-PINN—using space-time separation, random features instead of gradient descent, and incorporating temporal causality—was already presented prior to the original paper's submission. The candidate paper describes an identical methodology: space-time separation with frozen spatial basis functions, random feature sampling, and temporal causality enforcement through ODE solvers. The abstracts are nearly identical in their technical claims, suggesting this is not a novel contribution by the original authors.

Evidence

Evidence 1 - **Rationale**: This pair shows that Sampled Neural Networks[1] presents the exact same technical approach—space-time separation, random features, and temporal causality—demonstrating that this methodology existed prior to the original paper's claimed novelty. - **Original**: we present frozen-pinn, a novel pinn based on the principle of space-time separation that leverages random features instead of training with gradient descent, and incorporates temporal causality by construction. - **Candidate**: we present frozen-pinn, a novel pinn based on the principle of space-time separation that leverages random features instead of training with gradient descent, and incorporates temporal causality by construction.

Evidence 2 - **Rationale**: This identical claim about addressing PINN bottlenecks and achieving a combination that 'prior methods could not realize' appears in Sampled Neural Networks[1], refuting the original paper's claim to be the first to achieve this combination of features. - **Original**: our work addresses longstanding training and accuracy bottlenecks of pinns, delivering quickly trainable, highly accurate, and inherently causal pde solvers, a combination that prior methods could not realize. - **Candidate**: our work addresses longstanding training and accuracy bottlenecks of pinns, delivering quickly trainable, highly accurate, and inherently causal pde solvers, a combination that prior methods could not realize.

Evidence 3 - **Rationale**: The claim of challenging gradient-descent reliance and creating a paradigm shift is made identically in Sampled Neural Networks[1], demonstrating that this contribution was already established in prior work. - **Original**: our approach challenges the reliance of pinns on stochastic gradient-descent-based methods and specialized hardware, leading to a paradigm shift in pinn training and providing a challenging benchmark for the community. - **Candidate**: our approach challenges the reliance of pinns on stochastic gradient-descent-based methods and specialized hardware, leading to a paradigm shift in pinn training and providing a challenging benchmark for the community.

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5. Video reconstruction through dynamic scattering media based on physics-informed spatio-temporal transformer

URL: View paper

Brief Assessment

Scattering Media Transformer[72] focuses on video reconstruction through scattering media using transformers with physics-informed constraints, not on general PDE solving with space-time separation and random features for temporal causality as in Frozen-PINN.

Contribution 2: Adaptive solution-driven network parameters

Description: The method extends previous random feature approaches by computing neural network parameters adaptively using solution data from earlier time steps, enabling more efficient self-supervised PDE learning.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. TANTE: Time-Adaptive Operator Learning via Neural Taylor Expansion

URL: View paper

Brief Assessment

TANTE[61] focuses on adaptive time-stepping for operator learning via Taylor expansion, not on computing neural network parameters adaptively from previous time-step solution data for self-supervised PDE learning as in the original paper.

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2. Cell-Average Based Neural Network Method for Hunter-Saxton Equations

URL: View paper

Brief Assessment

Cell Average Hunter[65] uses supervised training with cell averages from a single initial value, not adaptive computation of network parameters from previous time-step solutions as in the original paper's self-supervised PDE learning approach.

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3. Adaptive multi-scale neural network with resnet blocks for solving partial differential equations

URL: View paper

Brief Assessment

Adaptive Multi Scale[67] focuses on using ResNet blocks for solving PDEs with multi-scale features, not on computing network parameters adaptively from previous time-step solution data for self-supervised PDE learning.

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4. Sinenet: Learning temporal dynamics in time-dependent partial differential equations

URL: View paper

Brief Assessment

SineNet[10] focuses on multi-stage U-Net architectures for temporal dynamics in PDEs, not on adaptive random feature methods using previous time-step solutions for self-supervised learning.

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5. FiniteNet: A fully convolutional LSTM network architecture for time-dependent partial differential equations

URL: View paper

Brief Assessment

FiniteNet[62] uses a fully convolutional LSTM architecture where network parameters are fixed after initialization and trained end-to-end on simulation data. The candidate does not compute network parameters adaptively using solution data from earlier time steps as described in the original contribution.

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6. A physics-informed recurrent neural network for solving time-dependent partial differential equations

URL: View paper

Prior Art Analysis

Physics Informed RNN[17] demonstrates prior work that computes neural network parameters adaptively using solution data from earlier time steps for PDE learning. The candidate explicitly states that 'the predicted values of the current layer are employed as the input of the next layer' and uses LSTM cells with 'parameter sharing' to ensure temporal continuity. This approach directly leverages previous time-step information to adapt network behavior, which predates the original paper's claim of extending random feature approaches by computing parameters adaptively using solution data from earlier time steps.

Evidence

Evidence 1 - **Rationale**: This pair demonstrates that Physics Informed RNN[17] already implements adaptive parameter computation using previous time-step solution data. The candidate explicitly uses 'predicted values of the current layer' as 'input of the next layer' to apply 'more information' for subsequent predictions, which is conceptually similar to the original's claim of computing parameters adaptively using solution data from earlier time steps. - **Original**: we use solution data from previous time-steps to compute efficient neural network parameters. this extends previous work on random feature methods (bolager et al., 2023) for self-supervised pde learning tasks. - **Candidate**: in order to preferably simulate the physical process and improve the accuracy of prediction, the predicted values of the current layer are employed as the input of the next layer, which exploits the idea of fdm. thus, more information can be applied for the next prediction, and the field values at d...

Evidence 2 - **Rationale**: This evidence shows that Physics Informed RNN[17] achieves efficient parameter computation through LSTM's parameter sharing mechanism, which inherently uses temporal information from previous steps. This predates the original's claim of computing 'efficient neural network parameters' using previous time-step data. - **Original**: adaptive solution-driven network parameters: we use solution data from previous time-steps to compute efficient neural network parameters. - **Candidate**: the number of the training parameters is sharply reduced due to the parameter sharing implemented in lstm cells so that the efficiency of pirnn greatly improves.

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7. A comprehensive study of non-adaptive and residual-based adaptive sampling for physics-informed neural networks

URL: View paper

Brief Assessment

Adaptive Sampling PINN[63] focuses on adaptive sampling strategies for collocation points in PINNs, not on computing neural network parameters adaptively using solution data from previous time steps as described in the original contribution.

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8. GrADE: A graph based data-driven solver for time-dependent nonlinear partial differential equations

URL: View paper

Brief Assessment

GrADE[66] uses graph neural networks with attention mechanisms for spatial modeling and neural ODEs for temporal evolution, but does not compute network parameters adaptively using solution data from earlier time steps in the manner described for the original paper's random feature approach.

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9. Temporal neural operator for modeling time-dependent physical phenomena

URL: View paper

Brief Assessment

Temporal Neural Operator[64] focuses on temporal extrapolation for time-dependent PDEs using a temporal branch architecture, not on adaptive random feature methods for self-supervised PDE learning as in the original paper.

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10. Surrogate Modeling and Parameter Inversion for Unsaturated Flow Based on implicit Time-Stepping Oriented Neural Network

URL: View paper

Brief Assessment

Unsaturated Flow Surrogate[68] focuses on implicit time-stepping for unsaturated flow problems in porous media, not on adaptive random feature methods for general PDE learning as in the original paper.

Contribution 3: SVD layer for model compression

Description: A singular value decomposition layer is added to reduce the dimensionality of the ODE system and improve computational efficiency by orthogonalizing basis functions, achieving significant compression and speedup.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

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1. ASVD: Activation-aware Singular Value Decomposition for Compressing Large Language Models

URL: View paper

Brief Assessment

ASVD[51] focuses on post-training compression of LLMs through weight matrix decomposition and KV cache reduction, not on dimensionality reduction of ODE systems in physics-informed neural networks for PDE solving.

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2. Learning low-rank deep neural networks via singular vector orthogonality regularization and singular value sparsification

URL: View paper

Brief Assessment

Low Rank Regularization[60] focuses on training neural networks with low-rank weight matrices via SVD decomposition and regularization techniques, not on reducing dimensionality of ODE systems in physics-informed neural networks as described in the original paper.

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3. Compressed neural networks for reduced order modeling

URL: View paper

Brief Assessment

Compressed Neural Networks[55] applies SVD to compress autoencoder networks for reduced order modeling of fluid flows, not for improving computational efficiency in ODE systems or orthogonalizing basis functions in physics-informed neural networks.

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4. Self-supervised knowledge distillation using singular value decomposition

URL: View paper

Brief Assessment

Self Supervised SVD[58] uses SVD for knowledge distillation in teacher-student networks, not for compressing ODE systems in PINNs. The technical contexts are fundamentally different—one addresses neural network training efficiency, the other addresses PDE solver architecture.

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5. Sparse low rank factorization for deep neural network compression

URL: View paper

Brief Assessment

Sparse Low Rank[54] applies SVD to fully connected layer weights for general neural network compression, whereas the original paper uses SVD to orthogonalize basis functions in a frozen-PINN architecture for reducing ODE system dimensionality in PDE solvers—fundamentally different applications and mechanisms.

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6. Optimal experimental design for universal differential equations

URL: View paper

Brief Assessment

Optimal Experimental Design[53] uses SVD for dimensionality reduction of the Fisher Information Matrix in the context of optimal experimental design for universal differential equations, not for neural network compression in ODE systems as described in the original paper's frozen-PINN architecture.

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7. SVD-LLM: Truncation-aware Singular Value Decomposition for Large Language Model Compression

URL: View paper

Brief Assessment

SVD LLM[52] focuses on post-training compression of large language models using SVD-based weight matrix decomposition, while the original paper uses SVD to orthogonalize basis functions in physics-informed neural networks for solving PDEs. These are fundamentally different applications and technical contexts.

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8. Learning Data-driven Reduced-order Models of Complex Flows

URL: View paper

Brief Assessment

Data Driven Reduced[59] discusses SVD for data dimension reduction in reduced-order modeling contexts, not as a neural network layer for ODE system compression with orthogonalized basis functions as in the original paper.

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9. Accelerating neural odes using model order reduction

URL: View paper

Brief Assessment

Accelerating Neural ODEs[56] applies SVD for weight truncation in neural ODE compression, not for dimensionality reduction of ODE systems through orthogonalized basis functions as in the original paper's SVD layer approach.

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10. Building symmetries into data-driven manifold dynamics models for complex flows

URL: View paper

Brief Assessment

Symmetries Manifold Dynamics[57] uses SVD for orthogonalizing basis functions in the context of symmetry-reduced manifold dynamics for fluid flows, not for general neural network compression or ODE systems as described in the original contribution.

Appendix: Text Similarity Detection

Textual similarity detection checked 27 papers and found 1 similarity segment(s) across 1 paper(s).

The following **1 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Solving partial differential equations with sampled neural networks

Detected in: Core Task (sibling), Contribution: contribution_1

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

- [0] Fast training of accurate physics-informed neural networks without gradient descent View paper
- [1] Solving partial differential equations with sampled neural networks View paper
- [2] GraphDeepONet: Learning to simulate time-dependent partial differential equations using graph neural network and deep operator network View paper
- [3] Real-time full-field estimation of transient responses in time-dependent partial differential equations using causal physics-informed neural networks with sparse â¦ View paper
- [4] Neural time-dependent partial differential equation View paper
- [5] Deep learning methods for modeling of spatiotemporal dynamical systems governed by partial differential equations View paper
- [6] Learning in modal space: Solving time-dependent stochastic PDEs using physics-informed neural networks View paper
- [7] Machine-learning-based spectral methods for partial differential equations View paper
- [8] Solving second-order nonlinear evolution partial differential equations using deep learning View paper
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