Physics-Informed Learning Machines Literature

455 Citations from my *Physics of Data* Obsidian vault

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Table of Contents

Citation Bibliography - PhysicsOfData Vault

Total Citations Found: 455

Categorization Summary

Scientific Machine Learning (Core): 404 papers

Supporting Papers: 51 papers

DataFrame Analysis

Year range: 1915 - 2024

Citations with Git repositories: 148

Citation types: - Paper : 398 - Book : 19 - Software : 10 - Slides : 6 - Chapter : 4

Citation Bibliography

Format: lastname, lastname. year. *title*. journal. N pages. DOI: DOI url. Relevance: score. [Git Repo].

1. Physics-Informed Learning Machines, SciML, PINNs

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13. Cai, Mao, Wang, Yin, Karniadakis. 2021. *Physics-informed neural networks (PINNs) for fluid mechanics: A review. . ODE-Net*. The Chinese Society of Theoretical and Applied Mechanics (CSTAM) 2020. 12 pages. DOI: https://doi.org/10.48550/arXiv.2105.09506. Relevance: 51.58.

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Processing Summary

Files generated:

- `citations.bib` - BibTeX bibliography file
- `citations_dataframe.csv` - Structured dataset for analysis
- `piml-citations-455.html` - HTML web report
- `piml-citations-455.pdf` - PDF report

Vault citations folder statistics:

- Referenced folder: 404 papers
- Supporting folder: 51 papers
- Unreferenced folder: 0 papers
- Scientific ML core papers: 404 papers
- Supporting papers: 51 papers
- No rated papers: 0 papers