Physics-Informed Learning Machines Literature

Citations from *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): 405 papers

Supporting Papers: 50 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.

1. Physics-Informed Learning Machines, SciML, PINNs

1. Wang, Wang, Perdikaris 2021. *Learning the solution operator of parametric partial differential equations with physics-informed DeepONets*. Science Advances. 29 Sep 2021. Vol 7, Issue 40. 9 pages. DOI: https://doi.org/10.1126/sciadv.abi8605. Relevance: 111.44.

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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: 19 papers
- Unreferenced folder: 436 papers
- Scientific ML core papers: 405 papers
- Supporting papers: 50 papers
- No rated papers: 0 papers