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

Complete Document Type Distribution:

- Paper: 397 • Book: 19 • Chapter: 4 • Slides: 6
- PhDThesis: 3 • MastersThesis: 1 • BScThesis: 2 • Patent: 1
- TechReport: 3 • Software: 10 • Video: 3 • Not Specified: 6

Top 5 Document Types: • Paper : 397 (87.3 %) • Book : 19 (4.2 %) • Software : 10 (2.2 %) • Slides : 6 (1.3 %) • Chapter : 4 (0.9 %)

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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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