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: 151

Complete Document Type Distribution:

- Paper: 393 • Book: 20 • Chapter: 5 • Slides: 6
- PhDThesis: 4 • MastersThesis: 1 • BScThesis: 2 • Patent: 1
- TechReport: 4 • Software: 9 • Video: 3 • Not Specified: 6
- Article : 1 citations

Top 5 Document Types: • Paper : 393 (86.4 %) • Book : 20 (4.4 %) • Software : 9 (2 %) • Slides : 6 (1.3 %) • Chapter : 5 (1.1 %)

Citation Bibliography

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

1. Physics-Informed Learning Machines, SciML, PINNs

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