Physics-Informed Learning Machines Literature

Citations from my *Physics of Data* Obsidian vault

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Citation Bibliography - PhysicsOfData Vault

Executive Summary

Total Citations Found: 518

Table 1: Citation Categorization Summary

Category	Number of Citations	Percentage
Scientific Machine Learning (Core)	462	89.2%
Supporting Papers	56	10.8%

Bibliometric Analysis

Table 2: Temporal and Repository Coverage

Metric	Value
Publication Year Range	1915 - 2025
Median Publication Year	2019
Most Productive Decade	2020s (246 citations)
Citations with Git Repositories	158
Repository Coverage Rate	30.5%
Citations with Reference Counts	494
Reference Data Coverage	95.4%
Average References per Citation	61
Citations with KDensity Scores	518
KDensity Coverage Rate	100%

Table 3: Quality and Impact Metrics

Metric	Value
Avg. KDensity - Scientific Machine Learning (Core)	28.27
Avg. KDensity - Supporting Papers	3.47
Citations with Highlights in PDF	332
PDF Highlights Coverage	64.1%
Citations with Keyword Matches	508
Keyword Match Coverage	98.1%

Table 4: Journal and Publisher Distribution

Publisher/Source	N	Percentage
arXiv Preprint	182	35.1%
Elsevier	101	19.5%
Other Publishers	76	14.7%
Springer	27	5.2%
Nature Publishing	20	3.9%
Conference Proceedings	15	2.9%
IEEE	14	2.7%
Science/AAAS	14	2.7%
SIAM	12	2.3%
PNAS	11	2.1%
Not Specified	9	1.7%
Wiley	8	1.5%
APS (Physical Review)	7	1.4%
AIP Publishing	6	1.2%
ACM	5	1%

Table 5: Document Type Distribution

Document Type	N	Percentage
Paper	462	89.2%
Book	20	3.9%
Software	9	1.7%
Slides	6	1.2%
Chapter	5	1%
PhDThesis	4	0.8%
TechReport	4	0.8%
Video	3	0.6%
BScThesis	2	0.4%
Article	1	0.2%
MastersThesis	1	0.2%
Patent	1	0.2%

Citation Format Specification

Standard Format: Author(s), Year. *Title*. Journal/Publisher, Volume(Issue): Pages. DOI: [identifier]. KDensity: [score]. Repository: [URL]. References: [count].

Metadata Fields:

- **K-Density Score:** Kernel density estimation score for citation impact
- **Repository Link:** GitHub or institutional repository URL when available
- **Reference Count:** Number of references cited within the document

1. Physics-Informed Learning Machines, SciML, PINNs

1. Kong, Yamashita, Foggo, Yu. 2022. *Dynamic Parameter Estimation with Physics-based Neural Ordinary Differential Equations*. 5 pages. DOI: https://doi.org/10.1109/pesgm48719.2022.9916840. KDensity: 178.8. Refs: 20.
2. Lu, Meng, Mao, Karniadakis. 2019. *DeepXDE: A Deep Learning Library for Solving Differential Equations*. SIAM Review 63(1):208-228. 2 pages. DOI: https://doi.org/10.1137/19M1274067. KDensity: 157.5. Repo. Refs: 1.
3. 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. KDensity: 137.33. Repo. Refs: 74.
4. Jagtap, Karniadakis. 2020. *Extended Physics-Informed Neural Networks (XPINNs): A Generalized Space-Time Domain Decomposition Based Deep Learning Framework for Nonlinear Partial Differential Equations*. Communications in Computational Physics. Volume 28, Issue 5pp. 2002–2041. 6 pages. DOI: https://doi.org/10.4208/cicp.OA-2020-0164. KDensity: 134.99. Repo. Refs: 11.
5. Yuan, Ni, Deng, Hao. 2022. *A-PINN: Auxiliary physics informed neural networks for forward and inverse problems of nonlinear integro-differential equations*. Journal of Computational Physics. 21 pages. DOI: https://doi.org/10.1016/j.jcp.2022.111260. KDensity: 122.62. Repo. Refs: 48.
6. Chen, Sondak, Protopapas, Mattheakis, Liu, Agarwal, Giovanni. 2020. *NeuroDiffEq: A Python package for solving differential equations with neural networks*. Journal of Open Source Software, 5(46), 1931,. 3 pages. DOI: https://doi.org/10.21105/joss.01931. KDensity: 99.33. Repo. Refs: 10.
7. Arzani, Wang, D'Souza. 2021. *Uncovering near-wall blood flow from sparse data with physics-informed neural networks*. Physics of Fluids. 10 pages. DOI: https://doi.org/10.1063/5.0055600. KDensity: 98.4. Repo. Refs: 67.

8. Liu, Zhu, Lu, Sun, Wang. 2023. *Multi-resolution partial differential equations preserved learning framework for spatiotemporal dynamics.* Communication Physics. 19 pages. DOI: https://doi.org/10.1038/s42005-024-01521-z. KDensity: 98.05. Repo. Refs: 82.

9. Falas, Konstantinou, Michael. 2020. *Physics-Informed Neural Networks for Securing Water Distribution Systems.* 4 pages. DOI: https://doi.org/10.48550/arXiv.2009.08842. KDensity: 94.5. Refs: 16.

10. Karniadakis, Kevrekidis, Lu, Perdikaris, Wang, Yang. 2021. *Physics-informed machine learning.* Nature Reviews Physics. 20 pages. DOI: https://doi.org/10.1038/s42254-021-00314-5. KDensity: 87.86. Repo. Refs: 206.

11. Anumasa, Srijith. 2021. *Improving Robustness and Uncertainty Modelling in Neural Ordinary Differential Equations.* IEEE Explore. 9 pages. DOI: https://doi.org/10.48550/arXiv.2112.12707. KDensity: 86.56. Repo. Refs: 28.

12. Liu, Xiao, Si, Cao, Kumar, Hsieh. 2019. *Neural SDE: Stabilizing Neural ODE Networks with Stochastic Noise.* 15 pages. DOI: https://doi.org/10.48550/arXiv.1906.02355. KDensity: 79.13. Repo. Refs: 23.

13. Champion, Lusch, Kutz, Brunton. 2019. *Data-driven discovery of coordinates and governing equations.* Proc. Natl. Acad. Sci. U.S.A.116 (45) 22445-22451,. 7 pages. DOI: https://doi.org/10.1073/pnas.1906995116. KDensity: 76.58. Repo. Refs: 57.

14. Finlay, Jacobsen, Oberman. 2020. *How to train your neural ODE: the world of Jacobian and kinetic regularization.* Accepted to ICML 2020. 11 pages. DOI: https://doi.org/10.48550/arXiv.2002.02798. KDensity: 74.18. Refs: 38.

15. Fang. 2021. *A High-Efficient Hybrid Physics-Informed Neural Networks Based on Convolutional Neural Network.* IEEE Trans Neural Netw Learn Syst. 2022 Oct;33(10):5514-5526. 13 pages. DOI: https://doi.org/10.1109/tnnls.2021.3070878. KDensity: 73.09. Repo. Refs: 34.

16. Meng, Li, Zhang, Karniadakis. 2019. *PPINN: Parareal Physics-Informed Neural Network for time-dependent PDEs.* Computer Methods in Applied Mechanics and Engineering. Vol-

ume. 17 pages. DOI: https://doi.org/10.1016/j.cma.2020.113250. KDensity: 70.65. Refs: 25.

17. Zhu, Liu, Yan. 2021. *Machine learning for metal additive manufacturing: predicting temperature and melt pool fluid dynamics using physics-informed neural networks.* Computational Mechanics. Volume 67. Issue number 2. State Published - Feb 2021. 17 pages. DOI: https://doi.org/10.1007/s00466-020-01952-9. KDensity: 70.07. Refs: 119.

18. Yan, Du, Tan, Feng. 2020. *On Robustness of Neural Ordinary Differential Equations.* 15 pages. DOI: https://doi.org/10.48550/arXiv.1910.05513. KDensity: 69.06. Repo. Refs: 34.

19. Raissi, Perdikaris, Karniadakis. 2017. *Physics Informed Deep Learning (Part I): Data-driven Solutions of Nonlinear Partial Differential Equations.* 22 pages. DOI: https://doi.org/10.48550/arXiv.1711.10561. KDensity: 67.31. Repo. Refs: 24.

20. Raissi, Perdikaris, Karniadakis. 2017. *Physics Informed Deep Learning (Part II): Data-driven Discovery of Nonlinear Partial Differential Equations.* 19 pages. DOI: https://doi.org/10.48550/arXiv.1711.10566. KDensity: 67.16. Repo. Refs: 18.

21. Gao, Huang, Trask, Reza. 2020. *Physics-Informed Graph Neural Network for Circuit Compact Model Development.* Conference: Physics-Informed Graph Neural Network for Circuit Compact Model Development.. 4 pages. DOI: http://dx.doi.org/10.23919/SISPAD49475.2020.9241634. KDensity: 66.5. Refs: 13.

22. Bongard, Lipson. 2007. *Automated reverse engineering of nonlinear dynamical systems.* Proc Natl Acad Sci U S A. 2007 Jun 12;104(24):9943-8. 6 pages. DOI: https://doi.org/10.1073/pnas.0609476104. KDensity: 66.17. Refs: 49.

23. Zhao, Ding, Prakash. 2023. *PINNsFormer: A Transformer-Based Framework For Physics-Informed Neural Networks.* cs> arXiv:2307.11833. 17 pages. DOI: https://arxiv.org/abs/2307.11833v3. KDensity: 66.12. Refs: 46.

24. Cai, Wang, Wang, Perdikaris, Karniadakis. 2021. *Physics-Informed Neural Networks for Heat Transfer Problems.* Journal of Heat Transfer 143(6).. 12 pages. DOI: https://doi.org/10.1115/1.4050542. KDensity: 66. Refs: 59.

25. Li, İrsoy, Cardie, Xing. 2016. *Physics-Inspired Neural Networks for Efficient Device Compact Modeling.* IEEE Journal on Exploratory Solid-State Computational Devices and Circuits. 6 pages. DOI: https://doi.org/10.1109/JXCDC.2016.2636161. KDensity: 66. Repo. Refs: 11.

26. Rudy, Brunton, Proctor, Kutz. 2017. *Data-driven discovery of partial differential equations.* Science Advances. 26 Apr 2017. Vol 3, Issue 4.. 6 pages. DOI: https://doi.org/10.1126/sciadv.1602614. KDensity: 65.5. Repo. Refs: 50.

27. Fan, Xu, Darve. 2020. *Solving Inverse Problems in Steady State Navier-Stokes Equations using Deep Neural Networks.* 7 pages. DOI: https://doi.org/10.48550/arXiv.2008.13074. KDensity: 65.43. Repo. Refs: 22.

28. 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. KDensity: 64.92. Refs: 59.

29. Yu, Swaminathan, Ji, White. 2017. *A method for creating behavioral models of oscillators using augmented neural networks.* 2017 IEEE 26th Conference on Electrical Performance of Electronic Packaging and Systems (EPEPS). 3 pages. DOI: https://doi.org/10.1109/EPEPS.2017.8329714. KDensity: 63.33. Refs: 7.

30. Wang, Yang, Liu, Zhao, Liu, Wu, Banu, Chen. 2022. *Data-driven modeling of process, structure and property in additive manufacturing: A review and future directions.* Journal of Manufacturing Processes 77 (2022) 13–31. 19 pages. DOI: https://doi.org/10.1016/j.jmapro.2022.02.053. KDensity: 62.94. Repo. Refs: 169.

31. Dolean, Heinlein, Mishra, Moseley. 2024. *Multilevel domain decomposition-based architectures for physics-informed neural networks.* Computer Methods in Applied Mechanics and Engineering 429 (2024) 117116. 21 pages. DOI: https://doi.org/10.1016/j.cma.2024.117116. KDensity: 62.23. Repo. Refs: 62.

32. Han, Jentzen, E. 2018. *Solving high-dimensional partial differential equations using deep learning.* Han J, Jentzen A, Weinan E. . Proc Natl Acad Sci 2018;115:8505–10.. 6 pages. DOI: https://doi.org/10.1073/pnas.1718942115. KDensity: 62.16. Refs: 32.

33. Matthews, Bihlo. 2024. *PinnDE: Physics-Informed Neural Networks for Solving Differential Equations.* Fluid Dynamics (physics.flu-dyn); Machine Learning (cs.LG). 17 pages. DOI: https://doi.org/10.48550/arXiv.2408.10011. KDensity: 61.42. Refs: 44.

34. Faroughi, Mostajeran, Mashhadzadeh, Faroughi. 2025. *Scientific Machine Learning with Kolmogorov-Arnold Networks.* Machine Learning (cs.LG); Computational Engineering, Finance, and Science (cs.CE); Mathematical Physics (math-ph). 44 pages. DOI: https://doi.org/10.48550/arXiv.2507.22959. KDensity: 59.01. Refs: 241.

35. Brunton, Hemati, Tair. 2020. *Special issue on machine learning and data-driven methods in fluid dynamics.* Theoretical and Computational Fluid Dynamics.. 5 pages. DOI: https://doi.org/10.1007/s00162-020-00542-y. KDensity: 58.8. Refs: 28.

36. Pacific-Northwest-National-Laboratory. 2020. *PhILMs: Collaboratory on Mathematics and Physics-Informed Learning Machines for Multiscale and Multiphysics Problems.* 40 pages. DOI: NA. KDensity: 56.35. Repo. Refs: 68.

37. Kim, Kim, Lee, Lee. 2021. *Knowledge Integration into deep learning in dynamical systems: an overview and taxonomy.* J Mech Sci Technol. 13 pages. DOI: https://doi.org/10.1007/s12206-021-0342-5. KDensity: 53.81. Refs: 72.

38. Heiden, Millard, Coumans, Sheng, Sukhatme. 2021. *Neuralsim: Augmenting differentiable simulators with neural networks.* 2021 IEEE International Conference onRobotics and Automation (ICRA), IEEE, 2021, pp. 9474–9481.. 8 pages. DOI: https://doi.org/10.48550/arXiv.2011.04217. KDensity: 53.5. Repo. Refs: 64.

39. Ruthotto, Haber. 2018. *Deep Neural Networks Motivated by Partial Differential Equations.* Journal of Mathematical Imaging and Vision. 8 pages. DOI: https://doi.org/10.1007/s10851-019-00903-1. KDensity: 52.87. Repo. Refs: 40.

40. Akbarian, Raissi. 2023. *PINNs-Torch: Enhancing Speed and Usability of Physics-Informed Neural Networks with PyTorch.* NeurIPS 2023 Workshop. 14 pages. DOI: https://openreview.net/forum?id=nl1ZzdHpab. KDensity: 52.14. Repo. Refs: 28.

41. Waheed, Haghighat, Alkhalifah, Song, Hao. 2021. *PINNeik: Eikonal solution using physics-*

informed neural networks. Computers & Geosciences. Volume 155, October. 14 pages. DOI: https://doi.org/10.1016/j.cageo.2021.104833. KDensity: 52.01. Repo. Refs: 64.

42. Psichogios, Ungar. 1992. *A hybrid neural network-first principles approach to process modeling.* AIChE J., 38: 1499-1511. 13 pages. DOI: https://doi.org/10.1002/aic.690381003. KDensity: 51.53. Refs: 31.

43. Dwivedi, Parashar, Srinivasan. 2021. *Distributed learning machines for solving forward and inverse problems in partial differential equations.* Neurocomputing. Volume. 18 pages. DOI: https://doi.org/10.1016/j.neucom.2020.09.006. KDensity: 51.5. Refs: 28.

44. Kochkov, Smith, Alieva, Wang, Brenner, Hoyer. 2021. *Machine learning accelerated computational fluid dynamics.* Proceedings of the National Academy of Sciences 118 (21) (2021).. 8 pages. DOI: https://doi.org/10.1073/pnas.2101784118. KDensity: 50.39. Repo. Refs: 56.

45. Jagtap, Mao, Adams, Karniadakis. 2022. *Physics-informed neural networks for inverse problems in supersonic flows.* math>arXiv:2202.11821. 19 pages. DOI: https://doi.org/10.1016/j.jcp.2022.111402. KDensity: 50.27. Refs: 46.

46. Zhang, Dao, Karniadakis, Suresh. 2022. *Analyses of internal structures and defects in materials using physics-informed neural networks.* Science Advances. 2022 Feb 18;8(7):eabk0644.doi: 10.1126/sciadv.abk0644. Epub 2022 Feb 16.. 13 pages. DOI: https://doi.org/10.1126/sciadv.abk0644. KDensity: 49.07. Refs: 64.

47. Hodas, Stinis. 2018. *Doing the Impossible: Why Neural Networks Can Be Trained at All.* Front. Psychol., 11 July 2018 Sec. Cognitive Science. Volume 9 - 2018. 7 pages. DOI: https://doi.org/10.3389/fpsyg.2018.01185. KDensity: 48.86. Repo. Refs: 23.

48. Akbarian, Raissi. 2023. *PINNs-TF2: Fast and User-Friendly Physics-Informed Neural Networks in TensorFlow V2.* Machine Learning and the Physical Sciences Workshop, NeurIPS 2023. 13 pages. DOI: https://arxiv.org/abs/2311.03626v1. KDensity: 48.31. Repo. Refs: 24.

49. Koryagin, Khudorozkov, Tsimfer. 2019. *PyDEns: a Python Framework for Solving Differential Equations with Neural Networks.* 8 pages. DOI: https://arxiv.org/abs/1909.11544. KDensity: 48.02. Repo. Refs: 9.

50. Brunton, Proctor, Kutz. 2016. *Sparse Identification of Nonlinear Dynamics with Control (SINDYc).* Accepted for NOLCOS conference. 6 pages. DOI: https://doi.org/10.48550/arXiv.1605.06682. KDensity: 47.99. Refs: 41.

51. Zhang, Yao, Gholami, Keutzer, Gonzalez, Biros, Mahoney. 2019. *ANODEV2: A Coupled Neural ODE Evolution Framework.* NeurIPS 2019 Workshop. 14 pages. DOI: https://doi.org/10.48550/arXiv.1906.04596. KDensity: 47.72. Refs: 25.

52. Kidger, Morrill, Foster, Lyons. 2020. *Neural Controlled Differential Equations for Irregular Time Series.* Advances in Neural Information Processing Systems 33 (NeurIPS 2020). 12 pages. DOI: https://doi.org/10.48550/arXiv.2005.08926. KDensity: 47.09. Repo. Refs: 74.

53. Kharazmi, Zhang, Karniadakis. 2019. *Variational Physics-Informed Neural Networks For Solving Partial Differential Equations.* arXiv e-prints. 24 pages. DOI: https://doi.org/10.48550/arXiv.1912.00873. KDensity: 46.75. Refs: 39.

54. Lu, Jin, Pang, Zhang, Karniadakis. 2021. *Learning nonlinear operators via DeepONet based on the universal approximation theorem of operators.* 15 pages. DOI: https://doi.org/10.1038/s42256-021-00302-5. KDensity: 46.34. Repo. Refs: 55.

55. Chen, Rubanova, Bettencourt, Duvenaud. 2018. *Neural Ordinary Differential Equations.* 32nd Conference on Neural Information Processing Systems (NeurIPS 2018), Montréal, Canada.. 18 pages. DOI: https://doi.org/10.48550/arXiv.1806.07366. KDensity: 46. Repo. Refs: 60.

56. Wang, Teng, Perdikaris. 2020. *Understanding and mitigating gradient pathologies in physics-informed neural networks.* NA. 28 pages. DOI: https://arxiv.org/abs/2001.04536v1. KDensity: 45.5. Repo. Refs: 54.

57. Yıldız, Heinonen, Lähdesmäki. 2019. *ODE2VAE: Deep generative second order ODEs with Bayesian neural networks.* 14 pages. DOI: https://doi.org/10.48550/arXiv.1905.10994.

KDensity: 45.21. Repo. Refs: 33.

58. Li, Zheng, Kovachki, Jin, Chen, Liu, Azizzadenesheli, Anandkumar. 2021. *Physics-Informed Neural Operator for Learning Partial Differential Equations.* 27 pages. DOI: https://doi.org/10.48550/arXiv.2111.03794. KDensity: 45. Refs: 58.

59. Lettermann, Jurado, Betz, Wörgötter, Herzog. 2024. *Tutorial: a beginner's guide to building a representative model of dynamical systems using the adjoint method.* Communications Physics volume 7, Article number: 128 (2024). 14 pages. DOI: https://doi.org/10.1038/s42005-024-01606-9. KDensity: 44.78. Repo. Refs: 99.

60. Ren, Rao, Liu, Wang, Sun. 2020. *PhyCRNet: Physics-informed Convolutional-Recurrent Network for Solving Spatio-temporal PDEs.* Computer Methods in Applied Mechanics and Engineering. Volume. 21 pages. DOI: https://doi.org/10.1016/j.cma.2021.114399. KDensity: 44.61. Repo. Refs: 86.

61. Rasht-Behesht, Huber, Shukla, Karniadakis. 2021. *Physics-Informed Neural Networks (PINNs) for Wave Propagation and Full Waveform Inversions.* Journal of Geophysical Research: Solid Earth, 127. 21 pages. DOI: https://doi.org/10.1029/2021JB023120. KDensity: 44.58. Refs: 54.

62. Li, Kovachki, Azizzadenesheli, Liu, Bhattacharya, Stuart, Anandkumar. 2021. *Fourier Neural Operator for Parametric Partial Differential Equations.* Published as a conference paper at ICLR 2021. 16 pages. DOI: https://doi.org/10.48550/arXiv.2010.08895. KDensity: 44.57. Refs: 34.

63. Jagtap, Kawaguchi, Karniadakis. 2019. *Locally adaptive activation functions with slope recovery term for deep and physics-informed neural networks.* Proc Math Phys Eng Sci. 2020 Jul 15; 476(2239):20200334.. 20 pages. DOI: https://doi.org/10.1098/rspa.2020.0334. KDensity: 44.25. Repo. Refs: 27.

64. Adeli. 2001. *Neural Networks in Civil Engineering: 1989–2000.* Comput. Aided Civ. Inf. Eng.. 17 pages. DOI: https://doi.org/10.1111/0885-9507.00219. KDensity: 43.65. Refs: 219.

65. Chang, Meng, Haber, Ruthotto, Begert, Holtham. 2017. *Reversible Architectures for Arbi-*

trarily Deep Residual Neural Networks. The Thirty-Second AAAI Conference on Artificial Intelligence (AAAI-18). 8 pages. DOI: http://10.1609/aaai.v32i1.11668. KDensity: 43.64. Refs: 49.

66. Cong, Li, Sun, Ren. 2025. *Using physics-informed derivative networks to solve the forward problem of a free-convective boundary layer problem*. Scientific Reports volume 15, Article number: 18766 (2025). 9 pages. DOI: https://doi.org/10.1038/s41598-025-03918-4. KDensity: 43.33. Refs: 31.

67. Artrith, Butler, Coudert, Han, Isayev, Jain, Walsh. 2021. *Best practices in machine learning for chemistry*. (2021) .Nat Chem 13:505–508. 4 pages. DOI: https://doi.org/10.1038/s41557-021-00716-z. KDensity: 43. Refs: 34.

68. Matsubara, Yaguchi. 2023. *Number Theoretic Accelerated Learning of Physics-Informed Neural Networks*. cs> arXiv:2307.13869. 14 pages. DOI: https://arxiv.org/abs/2307.13869v2. KDensity: 42.93. Refs: 55.

69. Al-Adly, Kripakaran. 2025. *Developing physics-informed neural networks for virtual sensing in beams with moving loads*. Engineering Structures. Volume. 20 pages. DOI: https://doi.org/10.1016/j.engstruct.2025.120535. KDensity: 42.1. Refs: 62.

70. Florio, Schiassi, Furfaro. 2022. *Physics-Informed Neural Networks and Functional Interpolation for Initial Value Problems with Applications to Integro-Differential and Stiff Differential Equations*. AIP Chaos. 18 pages. DOI: https://doi.org/10.1063/5.0086649. KDensity: 42.05. Repo. Refs: 53.

71. Jia, Benson. 2019. *Neural Jump Stochastic Differential Equations*. Advances in Neural Information Processing Systems 32 (NeurIPS 2019). 12 pages. DOI: NA. KDensity: 41.83. Repo. Refs: 45.

72. Penwarden, Zhe, Narayan, Kirby. 2021. *Multifidelity Modeling for Physics-Informed Neural Networks (PINNs)*. physics> arXiv:2106.13361. 17 pages. DOI: https://arxiv.org/abs/2106.13361v2. KDensity: 41.47. Refs: 44.

73. Tang, Chen, Lou, Fan, Yu, Nonaka, Yao, Gao. 2025. *Optical neural engine for solving sci-*

entific partial differential equations. Nature Communications volume 16, Article number: 4603 (2025). 13 pages. DOI: https://doi.org/10.1038/s41467-025-59847-3. KDensity: 41.3. Refs: 55.

74. Zou, Wang, Karniadakis. 2025. *Learning and discovering multiple solutions using physics-informed neural networks with random initialization and deep ensemble.* Machine Learning (cs.LG); Computational Physics (physics.comp-ph). 23 pages. DOI: https://doi.org/10.48550/arXiv.2503.06320. KDensity: 41.13. Refs: 95.

75. Shukla, Jagtap, Karniadakis. 2021. *Parallel Physics-Informed Neural Networks via Domain Decomposition.* arXiv [Submitted on 20 Apr 2021 (v1), last revised 8 Sep 2021 (this version, v3)]. 23 pages. DOI: https://arxiv.org/abs/2104.10013v3. KDensity: 41. Refs: 40.

76. Lu, Zhong, Li, Dong. 2018. *Beyond Finite Layer Neural Networks: Bridging Deep Architectures and Numerical Differential Equations.* Proceedings of the 35th International Conference on Machine Learning, PMLR 80:3276-3285, 2018.. 15 pages. DOI: https://doi.org/10.48550/arXiv.1710.10121. KDensity: 40.87. Repo. Refs: 52.

77. Kossaifi, Kovachki, Li, Pitt, Liu-Schiaffini, George, Bonev, Azizzadenesheli, Berner, Anandkumar. 2024. *A Library for Learning Neural Operators.* Machine Learning (cs.LG); Artificial Intelligence (cs.AI). 6 pages. DOI: https://doi.org/10.48550/arXiv.2412.10354. KDensity: 40.66. Refs: 22.

78. Toscano, Oommen, Varghese, Zou, Daryakenari, Wu, Karniadakis. 2024. *From PINNs to PIKANs: Recent Advances in Physics-Informed Machine Learning.* Machine Learning (cs.LG); Artificial Intelligence (cs.AI); Computational Physics (physics.comp-ph). 90 pages. DOI: https://doi.org/10.48550/arXiv.2410.13228. KDensity: 40.52. Refs: 416.

79. McClenny, Haile, Braga-Neto. 2021. *TensorDiffEq: Scalable Multi-GPU Forward and Inverse Solvers for Physics Informed Neural Networks.* arxiv [Submitted on 30 Mar 2021]. 8 pages. DOI: https://arxiv.org/abs/2103.16034v1. KDensity: 40.38. Refs: 24.

80. Darbon, Meng. 2020. *On some neural network architectures that can represent viscosity solutions of certain high dimensional Hamilton–Jacobi partial differential equations.* Journal of Computational Physics. Volume. 18 pages. DOI: https://doi.org/10.1016/j.jcp.2020.109

907. KDensity: 40.27. Repo. Refs: 118.

81. Cuomo, Cola, Giampaolo, Rozza, Raissi, Piccialli. 2022. *Scientific Machine Learning Through Physics-Informed Neural Networks: Where we are and What's Next.* 85 pages. DOI: https://doi.org/10.1007/s10915-022-01939-z. KDensity: 40.2. Repo. Refs: 196.

82. Pacific, Laboratory. 2021. *PhILMS: Collaboratory on Mathematics and Physics-Informed Learning Machines for Multiscale and Multiphysics Problems.* October 2021. 47 pages. DOI: NA. KDensity: 40.09. Repo. Refs: 63.

83. Jagtap, Kharazmi, Karniadakis. 2020. *Conservative physics-informed neural networks on discrete domains for conservation laws: Applications to forward and inverse problems.* Computer Methods in Applied Mechanics and Engineering. Volume. 27 pages. DOI: https://doi.org/10.1016/j.cma.2020.113028. KDensity: 40.08. Refs: 30.

84. Liu, Sun, Wang. 2022. *Predicting parametric spatio-temporal dynamics by multi-resolution PDE structure-preserved deep learning.* Commun Phys. 41 pages. DOI: http://dx.doi.org/10.48550/arXiv.2205.03990. KDensity: 40.08. Refs: 72.

85. Gafoor, Boya, Jinka, Gupta, Tyagi, Sarkar, Subramani. 2025. *A physics-informed neural network for turbulent wake simulations behind wind turbines.* Physics of Fluids. 23 pages. DOI: https://doi.org/10.1063/5.0245113. KDensity: 40.03. Repo. Refs: 97.

86. Yang, Meng, Karniadakis. 2021. *B-PINNs: Bayesian physics-informed neural networks for forward and inverse PDE problems with noisy data.* Journal of Computational Physics. Volume. 32 pages. DOI: https://doi.org/10.1016/j.jcp.2020.109913. KDensity: 39.94. Refs: 31.

87. Wang. 2024. *Scientific Machine Learning for Computational Physics.* SHTC Short Course, Anaheim, CA, July. 103 pages. DOI: NA. KDensity: 39.83. Refs: 40.

88. Rubanova, Chen, Duvenaud. 2019. *Latent ODEs for Irregularly-Sampled Time Series.* 21 pages. DOI: https://doi.org/10.48550/arXiv.1907.03907. KDensity: 39.81. Repo. Refs: 18.

89. Butler, Davies, Cartwright, Isayev, Walsh. 2018. *Machine learning for molecular and materials science.* Nature. 10 pages. DOI: http://dx.doi.org/10.1038/s41586-018-0337-2.

KDensity: 39.7. Repo. Refs: 99.

90. Rackauckas, Nie. 2017. *DifferentialEquations.jl – A Performant and Feature-Rich Ecosystem for Solving Differential Equations in Julia.* Journal of Open Research Software 5(1). 10 pages. DOI: https://doi.org/10.5334/jors.151. KDensity: 39.6. Refs: 30.

91. Sun, Gao, Pan, Wang. 2019. *Surrogate Modeling for Fluid Flows Based on Physics-Constrained Deep Learning Without Simulation Data.* Computer Methods in Applied Mechanics and Engineering. 56 pages. DOI: https://doi.org/10.1016/j.cma.2019.112732. KDensity: 39.44. Repo. Refs: 79.

92. Reyes, Howard, Perdikaris, Tartakovsky. 2020. *Learning unknown physics of non-Newtonian fluids.* Phys. Rev. Fluids. 6 pages. DOI: https://doi.org/10.1103/PhysRevFluids.6.073301. KDensity: 39. Refs: 23.

93. Cheng, Zhang. 2021. *Deep Learning Method Based on Physics Informed Neural Network with Resnet Block for Solving Fluid Flow Problems.* Water 13, no. 4: 423. 17 pages. DOI: https://doi.org/10.3390/w13040423. KDensity: 38.76. Refs: 30.

94. Lusch, Kutz, Brunton. 2018. *Deep learning for universal linear embeddings of nonlinear dynamics.* Nature Communications volume 9, Article number: 4950 (2018). 10 pages. DOI: https://doi.org/10.1038/s41467-018-07210-0. KDensity: 38.5. Repo. Refs: 56.

95. Berardi, Difonzo, Icardi. 2025. *Inverse Physics-Informed Neural Networks for transport models in porous materials.* Computer Methods in Applied Mechanics and Engineering. Volume. 15 pages. DOI: https://doi.org/10.1016/j.cma.2024.117628. KDensity: 38.19. Refs: 60.

96. Sun, Wang. 2020. *Physics-constrained bayesian neural network for fluid flow reconstruction with sparse and noisy data.* 9 pages. DOI: https://doi.org/10.1016/j.taml.2020.01.031. KDensity: 38.11. Repo. Refs: 41.

97. Detorakis. 2024. *Practical Aspects on Solving Differential Equations Using Deep Learning: A Primer.* 32 pages. DOI: https://arxiv.org/abs/2408.11266v2. KDensity: 38.04. Repo. Refs: 67.

98. Wong, Ooi, Gupta, Chiu, Low, Dao, Ong. 2023. *Generalizable Neural Physics Solvers by Baldwinian Evolution.* Neural and Evolutionary Computing. 26 pages. DOI: https://doi.org/10.48550/arXiv.2312.03243. KDensity: 38. Repo. Refs: 50.

99. Jeong, Batuwatta-Gamage, Bai, Xie, Rathnayaka, Zhou, Gu. 2023. *A complete Physics-Informed Neural Network-based framework for structural topology optimization.* Computer Methods in Applied Mechanics and Engineering. Volume 417, Part A, 1 December. 22 pages. DOI: https://doi.org/10.1016/j.cma.2023.116401. KDensity: 37.95. Refs: 81.

100. Mkadem, Boumaiza. 2011. *Physically Inspired Neural Network Model for RF Power Amplifier Behavioral Modeling and Digital Predistortion.* IEEE Transactions on Microwave Theory and Techniques, vol. 59, no. 4, pp. 913-923, April 2011. 13 pages. DOI: https://doi.org/10.1109/TMTT.2010.2098041. KDensity: 37.88. Refs: 38.

101. Trask, G.Patel, Gross, Atzberger. 2020. *GMLS-Nets: A machine learning framework for unstructured data.* AAAI-MLPS Proceedings, (2020). 9 pages. DOI: https://doi.org/10.48550/arXiv.1909.05371. KDensity: 37.78. Repo. Refs: 30.

102. Yu, Lu, Meng, Karniadakis. 2021. *Gradient-enhanced physics-informed neural networks for forward and inverse PDE problems.* Computer Methods in Applied Mechanics and Engineering. Volume. 22 pages. DOI: https://doi.org/10.1016/j.cma.2022.114823. KDensity: 37.46. Refs: 34.

103. Stiller, Bethke, Böhme, Pausch, Torge, Debus, Vorberger, Bussmann, Hoffmann. 2020. *Large-Scale Neural Solvers for Partial Differential Equations.* Driving Scientific and Engineering Discoveries Through the Convergence of HPC, Big Data and AI. SMC 2020. Communications in Computer and Information Science, vol 1315. Springer,. 15 pages. DOI: https://doi.org/10.1007/978-3-030-63393-6_2. KDensity: 37.07. Repo. Refs: 13.

104. Mojgani, Balajewicz, Hassanzadeh. 2023. *Kolmogorov n–width and Lagrangian physics-informed neural networks: A causality-conforming manifold for convection-dominated PDEs.* Computer Methods in Applied Mechanics and Engineering. Volume. 30 pages. DOI: https://doi.org/10.1016/j.cma.2022.115810. KDensity: 37.04. Repo. Refs: 82.

105. Raissi, Perdikaris, Karniadakis. 2019. *Physics-informed neural networks: A deep learning*

framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, vol. 378, pp. 686–707, 2019.. 45 pages. DOI: https://doi.org/10.1016/j.jcp.2018.10.045. KDensity: 36.77. Repo. Refs: 50.

106. Hochlehnert, Terenin, Sæmundsson, Deisenroth. 2021. *Learning contact dynamics using physically structured neural networks.* International Conference on Artificial In-telligence and Statistics, PMLR, 2021, pp. 2152–2160.. 10 pages. DOI: https://doi.org/10.48550/arXiv.2102.11206. KDensity: 36.5. Repo. Refs: 27.

107. Eshaghi, Anitescu, Thombre, Wang, Zhuang, Rabczuk. 2025. *Variational Physics-informed Neural Operator (VINO) for solving partial differential equations.* Computer Methods in Applied Mechanics and Engineering. Volume. 22 pages. DOI: https://doi.org/10.1016/j.cma.2025.117785. KDensity: 36.31. Repo. Refs: 59.

108. Keller. 2025. *Data-driven radiative hydrodynamics simulations of the solar photosphere using physics-informed neural networks: proof of concept.* Solar and Stellar Astrophysics (astro-ph.SR). 21 pages. DOI: https://doi.org/10.48550/arXiv.2505.04865. KDensity: 36.25. Refs: 27.

109. Martin, Peng, Mahoney. 2021. *Predicting trends in the quality of state-of-the-art neural networks without access to training or testing data.* Nature Communications volume 12, Article number: 4122 (2021). 13 pages. DOI: https://doi.org/10.1038/s41467-021-24025-8. KDensity: 36.23. Refs: 43.

110. Roth, Klein, Kannapinn, Peters, Weeger. 2025. *Stable Port-Hamiltonian Neural Networks.* cs> arXiv:2502.02480. 15 pages. DOI: https://doi.org/10.48550/arXiv.2502.02480. KDensity: 36.13. Refs: 53.

111. Rackauckas, Innes, Ma, Bettencourt, White, Dixit. 2019. *DiffEqFlux.jl - A Julia Library for Neural Differential Equations.* 17 pages. DOI: https://arxiv.org/abs/1902.02376v1. KDensity: 36.12. Refs: 7.

112. Moseley, Markham, Nissen-Meyer. 2023. *Finite basis physics-informed neural networks (FBPINNs): a scalable domain decomposition approach for solving differential equations.* Adv Comput Math. 39 pages. DOI: https://doi.org/10.1007/s10444-023-10065-9. KDensity:

36.08. Refs: 64.

113. van-Milligen, Tribaldos, Jiménez. 1995. *Neural Network Differential Equation and Plasma Equilibrium Solver.* Phys. Rev. Lett.. 4 pages. DOI: https://doi.org/10.1103/PhysRevLett.75.3594. KDensity: 35.75. Refs: 12.

114. Shin, Darbon, Karniadakis. 2020. *On the convergence of physics informed neural networks for linear second-order elliptic and parabolic type PDEs.* Communications in Computational Physics, Vol. 28 (2020), Iss. 5 : pp. 2042–2074. 31 pages. DOI: https://doi.org/10.48550/arXiv.2004.01806. KDensity: 35.58. Refs: 39.

115. Bram, Nahum, Schropp, Pfister, Koch. 2023. *Low-dimensional neural ODEs and their application in pharmacokinetics.* Journal of Pharmacokinetics and Pharmacodynamics. 18 pages. DOI: https://doi.org/10.1007/s10928-023-09886-4. KDensity: 35.56. Refs: 41.

116. Long, Lu, Ma, Dong. 2017. *PDE-Net: Learning PDEs from Data.* 17 pages. DOI: https://doi.org/10.48550/arXiv.1710.09668. KDensity: 35.52. Refs: 22.

117. Kobayashi, Park, Liu, Koric, Abueidda, Alam. 2025. *When Network Architecture Meets Physics: Deep Operator Learning for Coupled Multiphysics.* Machine Learning (cs.LG). 19 pages. DOI: https://doi.org/10.48550/arXiv.2507.03660. KDensity: 35. Refs: 65.

118. Um, Brand, Fei, Holl, Thuerey. 2020. *Solver-in-the-loop: Learning from differentiable physics to interact with iterative PDE-solvers.* Advances in Neural Information Processing Systems 33 (2020) 6111–6122.. 12 pages. DOI: https://doi.org/10.48550/arXiv.2007.00016. KDensity: 34.84. Repo. Refs: 67.

119. Kanaa, Voleti, Kahou, Pal. 2019. *Simple Video Generation using Neural ODEs.* NeurIPS 2019 Workshop. 10 pages. DOI: https://doi.org/10.48550/arXiv.2109.03292. KDensity: 34.6. Repo. Refs: 25.

120. Wang, Wang, Perdikaris. 2021. *On the eigenvector bias of Fourier feature networks: From regression to solving multi-scale PDEs with physics-informed neural networks.* Computer Methods in Applied Mechanics and Engineering. Volume. 27 pages. DOI: https://doi.org/10.1016/j.cma.2021.113938. KDensity: 34.52. Repo. Refs: 49.

121. Kosma, Nikolentzos, Panagopoulos, Steyaert, Vazirgiannis. 2023. *Neural Ordinary Differential Equations for Modeling Epidemic Spreading*. Published in Trans. Mach. Learn. Res. 2023. 18 pages. DOI: NA. KDensity: 34.44. Repo. Refs: 31.

122. Wang, Yu, Perdikaris. 2020. *When and why PINNs fail to train: A neural tangent kernel perspective*. Journal of Computational Physic. 29 pages. DOI: https://doi.org/10.1016/j.jcp.2021.110768. KDensity: 34.31. Repo. Refs: 47.

123. Cheng, Fu, Wang, Dong, Jin, Jiang, Maa, Qin, Liu. 2022. *Data-driven, multi-moment fluid modeling of Landau damping*. 10 pages. DOI: https://doi.org/10.48550/arXiv.2209.04726. KDensity: 34.3. Refs: 35.

124. Jagtap, Kawaguchi, Karniadakis. 2020. *Adaptive activation functions accelerate convergence in deep and physics-informed neural networks*. Journal of Computational Physics. Volume. 28 pages. DOI: https://doi.org/10.1016/j.jcp.2019.109136. KDensity: 34.17. Refs: 42.

125. Chen, Shi, He, Fang. 2024. *Data-driven solutions and parameter estimations of a family of higher-order KdV equations based on physics informed neural networks*. Scientific Reports. 27 pages. DOI: https://doi.org/10.1038/s41598-024-74600-4. KDensity: 34. Refs: 64.

126. Schmidhuber. 2015. *Deep learning in neural networks: An overview*. Neural Networks. Volume 61, January 2015, Pages 85-117. 33 pages. DOI: https://doi.org/10.1016/j.neunet.2014.09.003. KDensity: 33.97. Refs: 886.

127. LeCun, Bengio, Hinton. 2015. *Deep Learning*. Nature 521 (2015)436–444.. 10 pages. DOI: http://dx.doi.org/10.1038/nature14539. KDensity: 33.7. Repo. Refs: 103.

128. Brunton, Noack, Koumoutsakos. 2020. *Machine Learning for Fluid Mechanics*. Annual Review of Fluid Mechanics Volume. 32 pages. DOI: https://doi.org/10.1146/annurev-fluid-010719-060214. KDensity: 33.69. Refs: 169.

129. Chen, Lu, Karniadakis, Negro. 2020. *Physics-informed neural networks for inverse problems in nano-optics and metamaterials*. April 2020 Optics Express 28(8). 16 pages. DOI: https://doi.org/10.48550/arXiv.1912.01085. KDensity: 33.63. Refs: 40.

130. Shaviner, Chandravamsi, Pisnoy, Chen, Frankel. 2025. *PINNs for Solving Unsteady Maxwell's Equations: Convergence Issues and Comparative Assessment with Compact Schemes.* Computational Physics (physics.comp-ph). 18 pages. DOI: https://doi.org/10.48550/arXiv.2504.12144. KDensity: 33.6. Refs: 57.

131. Kashinath, Mustafa, Albert, Wu, Jiang, Esmaeilzadeh, Azizzadenesheli, Wang, Chattopadhyay, Singh, Manepalli, Chirila, Yu, Walters, White, Xiao, Tchelepi, Marcus, Anandkumar, Hassanzadeh. 2021. *Physics-informed machine learning: case studies for weather and climate modelling.* Royal Society Volume 379 Issue 2194. 36 pages. DOI: https://doi.org/10.1098/rsta.2020.0093. KDensity: 33.59. Repo. Refs: 130.

132. Abbasi, Jagtap, Moseley, Hiorth, Andersen. 2025. *Challenges and Advancements in Modeling Shock Fronts with Physics-Informed Neural Networks: A Review and Benchmarking Study.* Fluid Dynamics (physics.flu-dyn); Machine Learning (cs.LG). 37 pages. DOI: https://doi.org/10.48550/arXiv.2503.17379. KDensity: 33.51. Refs: 0.

133. Zhang, Gao, Unterman, Arodz. 2020. *Approximation Capabilities of Neural ODEs and Invertible Residual Networks.* Proceedings of the 37th International Conference on Machine Learning, PMLR 119:11086-11095. 14 pages. DOI: https://doi.org/10.48550/arXiv.1907.12998. KDensity: 33.36. Refs: 24.

134. Nath, Meng, Smith, Karniadakis. 2023. *Physics-informed neural networks for predicting gas flow dynamics and unknown parameters in diesel engines.* Sci Rep. 31 pages. DOI: https://doi.org/10.1038/s41598-023-39989-4. KDensity: 33.26. Refs: 24.

135. Al-Adly, Kripakaran. 2024. *Physics-informed neural networks for structural health monitoring: a case study for Kirchhoff–Love plates.* Published online by Cambridge University Press: 13 March 2024. 24 pages. DOI: https://doi.org/10.1017/dce.2024.4. KDensity: 33.17. Refs: 0.

136. McClenny, Braga-Neto. 2020. *Self-Adaptive Physics-Informed Neural Networks using a Soft Attention Mechanism.* cs> arXiv:2009.04544. 24 pages. DOI: https://arxiv.org/abs/2009.04544v5. KDensity: 33.09. Repo. Refs: 36.

137. Qin, Wu, Xiu. 2019. *Data Driven Governing Equations Approximation Using Deep Neural*

Networks. Journal of Computational Physics. Volume. 19 pages. DOI: https://doi.org/10.1016/j.jcp.2019.06.042. KDensity: 32.89. Refs: 54.

138. Hutchinson, Steiert, Soubret, Wagg, Phipps, Peck, Charoin, Ribba. 2019. *Models and machines: how deep learning will take clinical pharmacology to the next level.* (2019) . CPT-Pharmacometrics Syst Pharmacol. https://doi.org/10.1002/psp4.12377. 4 pages. DOI: https://doi.org/10.1002/psp4.12377. KDensity: 32.5. Refs: 10.

139. Zhang, Yin, Karniadakis. 2020. *Physics-Informed Neural Networks for Nonhomogeneous Material Identification in Elasticity Imaging.* arXiv. [Submitted on 2 Sep 2020]. 10 pages. DOI: https://arxiv.org/abs/2009.04525v1. KDensity: 32.5. Refs: 19.

140. O'Leary, Paulson, Mesbah. 2022. *Stochastic Physics-Informed Neural Ordinary Differential Equations.* Journal of Computational Physics. Vol. 468, No. C. 35 pages. DOI: https://doi.org/10.1016/j.jcp.2022.111466. KDensity: 32.45. Repo. Refs: 86.

141. Dupont, Doucet, Teh. 2019. *Augmented Neural ODEs.* 20 pages. DOI: https://doi.org/10.48550/arXiv.1904.01681. KDensity: 32.35. Repo. Refs: 22.

142. Cranmer, Greydanus, Hoyer, Battaglia, Spergel, Ho. 2020. *Lagrangian Neural Networks.* Published in ICLR 2020 Deep Differential Equations Workshop.. 9 pages. DOI: https://doi.org/10.48550/arXiv.2003.04630. KDensity: 32.33. Repo. Refs: 21.

143. Lai, Mylonas, Nagarajaiah, Chatzi. 2021. *Structural identification with physics-informed neural ordinary differential equations.* Journal of Sound and Vibration. Volume. 36 pages. DOI: https://doi.org/10.1016/j.jsv.2021.116196. KDensity: 32.28. Refs: 58.

144. Lagaris, Likas, Fotiadis. 1997. *Artificial Neural Networks for Solving Ordinary and Partial Differential Equations.* IEEE Transactions on Neural Networks (Volume: 9, Issue: 5, September 1998). 14 pages. DOI: https://doi.org/10.48550/arXiv.physics/9705023. KDensity: 31.72. Refs: 13.

145. Pang, Lu, Karniadakis. 2019. *fPINNs: Fractional Physics-Informed Neural Networks.* Methods and Algorithms for Scientific Computing. 29 pages. DOI: https://doi.org/10.1137/18M1229845. KDensity: 31.66. Refs: 68.

146. Rao, Sun, Liu. 2021. *Physics informed deep learning for computational elastodynamics without labeled data.* Journal of Engineering Mechanics 147 (8) (2021) 04021043.. 26 pages. DOI: https://arxiv.org/abs/2006.08472v1. KDensity: 31.5. Repo. Refs: 65.

147. Blechschmidt, Ernst. 2021. *Three ways to solve partial differential equations with neural networks - A review.* Volume 44, Issue 2 Special Issue:Scientific Machine Learning - Part II June 2021 e202100006. 29 pages. DOI: https://doi.org/10.1002/gamm.202100006. KDensity: 31.08. Repo. Refs: 183.

148. Li, Bragone, Barreau, Morozovska. 2025. *MILP initialization for solving parabolic PDEs with PINNs.* Machine Learning (cs.LG). 19 pages. DOI: https://doi.org/10.48550/arXiv.2501.16153. KDensity: 31. Refs: 22.

149. Wang, Sankaran, Wang, Perdikaris. 2023. *An Expert's Guide to Training Physics-informed Neural Networks.* cs>arXiv:2308.08468. 36 pages. DOI: https://arxiv.org/abs/2308.08468v1. KDensity: 30.7. Refs: 78.

150. Pascanu, Gulcehre, Cho, Bengio. 2014. *How to Construct Deep Recurrent Neural Networks.* Accepted at ICLR 2014 (Conference Track).. 13 pages. DOI: https://doi.org/10.48550/arXiv.1312.6026. KDensity: 30.69. Refs: 48.

151. Choi, Cheung, Kim, Tsai, Diaz, Zanardi, Chung, Copeland, Kendrick, Anderson, Iliescu, Heinkenschloss. 2025. *Defining Foundation Models for Computational Science: A Call for Clarity and Rigor.* cs> arXiv:2505.22904. 26 pages. DOI: https://doi.org/10.48550/arXiv.2505.22904. KDensity: 30.62. Refs: 62.

152. Erichson, Muehlebach, Mahoney. 2019. *Physics-informed Autoencoders for Lyapunov-stable Fluid Flow Prediction.* 14 pages. DOI: https://doi.org/10.48550/arXiv.1905.10866. KDensity: 30.29. Refs: 41.

153. Faroughia, Mostajerana. 2025. *Neural Tangent Kernel Analysis to Probe Convergence in Physics-informed Neural Solvers: PIKANs vs. PINNs.* Machine Learning (cs.LG); Mathematical Physics (math-ph); Analysis of PDEs (math.AP); Spectral Theory (math.SP). 30 pages. DOI: https://doi.org/10.48550/arXiv.2506.07958. KDensity: 30.2. Refs: 104.

154. Innes, Edelman, Fischer, Rackauckas, Saba, Shah, Tebbutt. 2019. *A Differentiable Programming System to Bridge Machine Learning and Scientific Computing.* Submitted to NeurIPS 2019. 14 pages. DOI: https://arxiv.org/abs/1907.07587v2. KDensity: 29.64. Repo. Refs: 49.

155. Cai, Wang, Fuest, Jeon, Gray, Karniadakis. 2021. *Flow over an espresso cup: inferring 3-D velocity and pressure fields from tomographic background oriented Schlieren via physics-informed neural networks.* Journal of Fluid Mechanics. 2021;915:A102. 17 pages. DOI: http://10.1017/jfm.2021.135. KDensity: 29.59. Refs: 33.

156. Alkin, Fürst, Schmid, Gruber, Holzleitner, Brandstetter. 2024. *Universal Physics Transformers: A Framework For Efficiently Scaling Neural Operators.* NeurIPS 2024. 37 pages. DOI: https://doi.org/10.48550/arXiv.2402.12365. KDensity: 29.54. Repo. Refs: 119.

157. Sun, Zhang, Schaeffer. 2020. *NeuPDE: Neural network based ordinary and partial differential equations for modeling time-dependent data.* Mathematical and ScientificMachine Learning, PMLR, 2020, pp. 352–372.. 21 pages. DOI: https://doi.org/10.48550/arXiv.1908.03190. KDensity: 29.48. Refs: 41.

158. Mishra, Molinaro. 2021. *Estimates on the generalization error of physics-informed neural networks for approximating a class of inverse problems for PDEs Get access Arrow.* IMA Journal of Numerical Analysis, Volume 42, Issue 2, April 2022, Pages 981–1022. 35 pages. DOI: https://doi.org/10.1093/imanum/drab032. KDensity: 29. Repo. Refs: 63.

159. Rudy, Alla, Brunton, Kutz. 2018. *Data-driven identification of parametric partial differential equations.* arxiv math arXiv:1806.00732. 17 pages. DOI: https://arxiv.org/abs/1806.00732v1. KDensity: 28.82. Refs: 63.

160. Paszke, Gross, Chintala, Chanan, Yang, DeVito, Lin, Desmaison, Antiga, Lerer. 2017. *Automatic differentiation in PyTorch.* NIPS 2017 Workshop Autodiff Decision Program Chairs. 4 pages. DOI: NA. KDensity: 28.75. Refs: 6.

161. Raissi, Perdikaris, Karniadakis. 2018. *Multistep Neural Networks for Data-driven Discovery of Nonlinear Dynamical Systems.* 19 pages. DOI: https://doi.org/10.48550/arXiv.1801.01236. KDensity: 28.74. Repo. Refs: 31.

162. Goswami, Anitescu, Chakraborty, Rabczuk. 2020. *Transfer learning enhanced physics informed neural network for phase-field modeling of fracture.* Theoretical and Applied Fracture Mechanics. Volume 106, April. 21 pages. DOI: https://doi.org/10.1016/j.tafmec.2019.102447. KDensity: 28.72. Refs: 28.

163. Kissas, Yang, Hwuang, Witschey, Detre, Perdikaris. 2020. *Machine learning in cardiovascular flows modeling: Predicting arterial blood pressure from non-invasive 4D flow MRI data using physics-informed neural networks.* Computer Methods in Applied Mechanics and Engineering. Volume. 30 pages. DOI: https://doi.org/10.1016/j.cma.2019.112623. KDensity: 28.7. Refs: 69.

164. Pathak, Wikner, Fussell, Chandra, Hunt, Girvan, Ott. 2018. *Hybrid Forecasting of Chaotic Processes: Using Machine Learning in Conjunction with a Knowledge-Based Model.* Chaos. 10 pages. DOI: https://doi.org/10.1063/1.5028373. KDensity: 28.59. Refs: 21.

165. Wang, Sankaran, Stinis, Perdikaris. 2025. *Simulating Three-dimensional Turbulence with Physics-informed Neural Networks.* Machine Learning (cs.LG); Artificial Intelligence (cs.AI); Computational Physics (physics.comp-ph); Fluid Dynamics (physics.flu-dyn). 24 pages. DOI: https://doi.org/10.48550/arXiv.2507.08972. KDensity: 28.5. Refs: 51.

166. Patra, Panda, Parida, Arya, Jacobs, Bondar, Sen. 2024. *Physics Informed Kolmogorov-Arnold Neural Networks for Dynamical Analysis via Efficent-KAN and WAV-KAN.* cs> arXiv:2407.18373. 18 pages. DOI: https://arxiv.org/abs/2407.18373v2. KDensity: 28.44. Refs: 50.

167. Pearlmutter. 1995. *Gradient calculations for dynamic recurrent neural networks: a survey.* IEEE Transactions on Neural Networks, vol. 6, no. 5, pp. 1212-1228, Sept. 1995. 21 pages. DOI: https://doi.org/10.1109/72.410363. KDensity: 28.26. Refs: 164.

168. Wang, Bai, Eshaghi, Anitescu, Zhuang, Rabczuk, Liu. 2025. *Transfer Learning in Physics-Informed Neurals Networks: Full Fine-Tuning, Lightweight Fine-Tuning, and Low-Rank Adaptation.* International Journal of Mechanical System Dynamics . Volume 5, Issue 2. June 2025. Pages 212-235. 24 pages. DOI: https://doi.org/10.1002/msd2.70030. KDensity: 28.21. Refs: 43.

169. Sirignano, Spiliopoulos. 2018. *DGM: A deep learning algorithm for solving partial differential equations*. Journal of Computational Physics. Volume. 31 pages. DOI: https://doi.org/10.1016/j.jcp.2018.08.029. KDensity: 28.1. Refs: 49.

170. Belbute-Peres, Economon, Kolter. 2020. *Combining differentiable PDE solvers and graph neural networks for fluid flow prediction*. International Conference on MachineLearning, PMLR, 2020, pp. 2402–2411.. 16 pages. DOI: https://doi.org/10.48550/arXiv.2007.04439. KDensity: 28.07. Repo. Refs: 25.

171. Csala, Mohan, Livescu, Arzani. 2025. *Physics-constrained coupled neural differential equations for one dimensional blood flow modeling*. Computers in Biology and Medicine. Volume 186, March. 29 pages. DOI: https://doi.org/10.1016/j.compbiomed.2024.109644. KDensity: 28.01. Refs: 0.

172. Gal, Ghahramani. 2016. *Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning*. Proceedings of The 33rd International Conference on Machine Learning, PMLR 48:1050-1059, 2016.. 10 pages. DOI: NA. KDensity: 28. Refs: 42.

173. Greydanus, Dzamba, Yosinski. 2019. *Hamiltonian Neural Networks*. Conference paper at NeurIPS 2019. 11 pages. DOI: https://doi.org/10.48550/arXiv.1906.01563. KDensity: 28. Repo. Refs: 45.

174. Haghighat, Raissi, Moure, Gomez, Juanes. 2021. *A physics-informed deep learning framework for inversion and surrogate modeling in solid mechanics*. Computer Methods in Applied Mechanics and Engineering. Volume. 22 pages. DOI: https://doi.org/10.1016/j.cma.2021.113741. KDensity: 28. Repo. Refs: 51.

175. Michoski, Milosavljevic, Oliver, Hatch. 2019. *Solving Irregular and Data-enriched Differential Equations using Deep Neural Networks*. 22 pages. DOI: https://doi.org/10.48550/arXiv.1905.04351. KDensity: 27.87. Refs: 61.

176. Schaeffer, Caflisch, Hauck, Osher. 2013. *Sparse dynamics for partial differential equations*. Applied Mathematics 110 (17) 6634-6639. 6 pages. DOI: https://doi.org/10.1073/pnas.1302752110. KDensity: 27.67. Refs: 18.

177. Utkarsh, Cai, Edelman, Gomez-Bombarelli, Rackauckas. 2025. *Physics-Constrained Flow Matching: Sampling Generative Models with Hard Constraints*. Machine Learning (cs.LG); Computational Engineering, Finance, and Science (cs.CE); Mathematical Physics (math-ph. 27 pages. DOI: https://doi.org/10.48550/arXiv.2506.04171. KDensity: 27.67. Refs: 72.

178. Zhang, Guo, Karniadakis. 2020. *Learning in Modal Space: Solving Time-Dependent Stochastic PDEs Using Physics-Informed Neural Networks*. SIAM Journal on Scientific Computing. Vol. 42, Iss. 2 (2020)10.1137/19M1260141. 31 pages. DOI: https://doi.org/10.1137/19M1260141. KDensity: 27.57. Refs: 30.

179. Hao, Wang, Su, Ying, Dong, Liu, Cheng, Song, Zhu. 2023. *GNOT: A general neural operator transformer for operator learning*. Proceedings of the 40th International Conference on Machine Learning, pp.12556–12569. PMLR, 2023.. 14 pages. DOI: https://doi.org/10.48550/arXiv.2302.14376. KDensity: 27.56. Repo. Refs: 38.

180. Ren, Rao, Chen, Wang, Sun, Liu. 2022. *SeismicNet: Physics-informed neural networks for seismic wave modeling in semi-infinite domain*. 22 pages. DOI: https://doi.org/10.48550/arXiv.2210.14044. KDensity: 27.54. Repo. Refs: 68.

181. Wang, Zeng, Wang, Shang, Zhang, Luo, Dowling. 2022. *When physics-informed data analytics outperforms black-box machine learning: A case study in thickness control for additive manufacturing*. Digital Chemical Engineering. 17 pages. DOI: https://doi.org/10.1016/j.dche.2022.100076. KDensity: 27.12. Refs: 60.

182. Hennigh, Narasimhan, Nabian, Subramaniam, Tangsali, Fang, Rietmann, Byeon, Choudhry. 2021. *NVIDIA SimNet: An AI-Accelerated Multi-Physics Simulation Framework*. ICCS 2021. ICCS 2021. Lecture Notes in Computer Science(), vol 12746.. 15 pages. DOI: https://doi.org/10.1007/978-3-030-77977-1_36. KDensity: 27.11. Repo. Refs: 20.

183. Ruthotto, Osher, Li, Nurbekyan, Fung. 2019. *A Machine Learning Framework for Solving High-Dimensional Mean Field Game and Mean Field Control Problems*. Proc. Natl. Acad. Sci. U.S.A.117 (17) 9183-9193,. 11 pages. DOI: https://doi.org/10.1073/pnas.1922204117. KDensity: 27.09. Repo. Refs: 81.

184. Graepel. 2003. *Solving Noisy Linear Operator Equations by Gaussian Processes: Application to Ordinary and Partial Differential Equations.* Proceedings of the Twentieth International Conference on Machine Learning. 8 pages. DOI: NA. KDensity: 27.01. Refs: 16.

185. Shukla, Leoni, Blackshire, Sparkman, Karniadakis. 2020. *Physics-informed neural network for ultrasound nondestructive quantification of surface breaking cracks.* arXiv. [Submitted on 7 May 2020]. 19 pages. DOI: https://arxiv.org/abs/2005.03596v1. KDensity: 26.99. Refs: 24.

186. Iftakher, Golder, Hasan. 2025. *Physics-Informed Neural Networks with Hard Nonlinear Equality and Inequality Constraints.* Machine Learning (cs.LG). 20 pages. DOI: https://doi.org/10.48550/arXiv.2507.08124. KDensity: 26.95. Refs: 44.

187. Krannichfeldt, Orehounig, Fink. 2025. *Combining physics-based and data-driven modeling for building energy systems.* Applied Energy. Volume. 19 pages. DOI: https://doi.org/10.1016/j.apenergy.2025.125853. KDensity: 26.85. Refs: 51.

188. Jia, Willard, Karpatne, Read, Zwart, Steinbach, Kumar. 2020. *Physics-Guided Machine Learning for Scientific Discovery: An Application in Simulating Lake Temperature Profiles.* ACM/IMS Transactions on Data Science, Volume 2, Issue 3. Article No.: 20, Pages 1 - 26. 26 pages. DOI: https://doi.org/10.1145/3447814. KDensity: 26.81. Refs: 62.

189. Moore, Wong, Giera, Oyarzun, Gongora, Lin, Li, Owens, Nguyen, Ehlinger, Chung, Roy, DeOtte, Cross, Aui, Choi, Goldman, Jeong, Ye, Sarkar, Duoss, Hahn, Baker. 2024. *Accelerating climate technologies through the science of scale-up.* Nature Chemical Engineering volume 1, pages 731–740 (2024). 10 pages. DOI: https://doi.org/10.1038/s44286-024-00143-0. KDensity: 26.6. Refs: 75.

190. Zhang, Liu, Sun. 2020. *Physics-informed multi-LSTM networks for metamodeling of nonlinear structures.* Computer Methods in Applied Mechanics and Engineering. Volume. 21 pages. DOI: https://doi.org/10.1016/j.cma.2020.113226. KDensity: 26.56. Repo. Refs: 63.

191. Kharazmi, Zhang, Karniadakis. 2021. *hp-VPINNs: Variational physics-informed neural networks with domain decomposition.* Computer Methods in Applied Mechanics and Engineering. Volume. 21 pages. DOI: https://doi.org/10.1016/j.cma.2020.113547. KDensity:

26.38. Refs: 46.

192. Aldakheel, Elsayed, Heider, Weeger. 2025. *Physics-based Machine Learning for Computational Fracture Mechanics.* math> arXiv:2502.09025. 20 pages. DOI: https://doi.org/10.48550/arXiv.2502.09025. KDensity: 26.3. Refs: 53.

193. Lu, Pestourie, Yao, Wang, Verdugo, Johnson. 2020. *Physics-Informed Neural Networks with Hard Constraints for Inverse Design.* SIAM Journal on Scientific Computing. Volume 43 • Issue 6 • January 2021. Pages: B1105 - B1132. 29 pages. DOI: https://doi.org/10.1137/21M1397908. KDensity: 26.03. Refs: 62.

194. Rahim, Al-Ramadhan. 2002. *Dynamic equivalent of external power system and its parameter estimation through artificial neural networks.* International Journal of Electrical Power & Energy Systems. Volume 24, Issue 2, February 2002, Pages 113-120. 7 pages. DOI: https://doi.org/10.1016/S0142-0615(01)00016-3. KDensity: 26.01. Refs: 15.

195. Mathews, Francisquez, Hughes, Hatch, Zhu, Rogers. 2021. *Uncovering turbulent plasma dynamics via deep learning from partial observations.* Phys. Rev. E. 11 pages. DOI: https://doi.org/10.1103/PhysRevE.104.025205. KDensity: 26. Repo. Refs: 55.

196. Raissi. 2017. *Parametric Gaussian Process Regression for Big Data.* arxiv [Submitted on 11 Apr 2017 (v1), last revised 4 May 2017 (this version, v2)]. 6 pages. DOI: https://arxiv.org/abs/1704.03144v2. KDensity: 26. Repo. Refs: 30.

197. Raissi. 2018. *Deep Hidden Physics Models: Deep Learning of Nonlinear Partial Differential Equations.* 26 pages. DOI: https://doi.org/10.48550/arXiv.1801.06637. KDensity: 25.96. Repo. Refs: 47.

198. De-Ryck, Jagtap, Mishra. 2022. *Error estimates for physics informed neural networks approximating the Navier-Stokes equations.* NA. 34 pages. DOI: https://doi.org/10.48550/arXiv.2203.09346. KDensity: 25.86. Refs: 48.

199. Han, Gao, Pfaff, Wang, Liu. 2022. *Predicting Physics in Mesh-reduced Space with Temporal Attention.* ICLR 2022. 22 pages. DOI: https://doi.org/10.48550/arXiv.2201.09113. KDensity: 25.85. Refs: 54.

200. Canizares, Murari, Schönlieb, Sherry, Shumaylov. 2024. *Symplectic Neural Flows for Modeling and Discovery.* Machine Learning (cs.LG); Computational Physics (physics.comp-ph); Fluid Dynamics (physics.flu-dyn). 26 pages. DOI: https://doi.org/10.48550/arXiv.2412.16787. KDensity: 25.57. Refs: 64.

201. Shi, Chen, Wang, Yeung, Wong, Woo. 2015. *Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting.* 9 pages. DOI: https://doi.org/10.48550/arXiv.1506.04214. KDensity: 25.56. Repo. Refs: 26.

202. Jin, Lu, Tang, Karniadakis. 2019. *Quantifying the generalization error in deep learning in terms of data distribution and neural network smoothness.* Neural Networks. Volume 130, October 2020, Pages 85-99. 17 pages. DOI: https://doi.org/10.1016/j.neunet.2020.06.024. KDensity: 25.41. Refs: 62.

203. Bahmani, Kevrekidis, Shields. 2025. *Neural Chaos: A Spectral Stochastic Neural Operator.* Computational Engineering, Finance, and Science (cs.CE); Computational Physics (physics.comp-ph); Machine Learning (stat.ML). 30 pages. DOI: https://doi.org/10.48550/arXiv.2502.11835. KDensity: 25.23. Refs: 48.

204. Huang, Wang, Lan. 2011. *Extreme learning machines: a survey.* International Journal of Machine Learning and Cybernetics 2(2):107–122. 16 pages. DOI: https://doi.org/10.1007/s13042-011-0019-y. KDensity: 25.07. Refs: 119.

205. Abadi, Agarwal, Barham, Brevdo, Chen, Citro, Corrado, Davis, Dean, Devin, Ghemawat, Goodfellow, Harp, Irving, Isard, Jia, Jozefowicz, Kaiser, Kudlur, Levenberg, Mane, Monga, Moore, Murray, Olah, Schuster, Shlens, Steiner, Sutskever, Talwar, Tucker, Vanhoucke, Vasudevan, Viegas, Vinyals, Warden, Wattenberg, Wicke, Yu, Zheng. 2016. *TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems.* 19 pages. DOI: https://arxiv.org/abs/1603.04467v2. KDensity: 24.85. Refs: 56.

206. Yin, Zheng, Humphrey, Karniadakis. 2021. *Non-invasive inference of thrombus material properties with physics-informed neural networks.* Computer Methods in Applied Mechanics and Engineering. 38 pages. DOI: https://doi.org/10.1016/j.cma.2020.113603. KDensity: 24.85. Refs: 63.

207. Brunton, Kutz, Manohar, Aravkin, Morgansen, Klemisch, Goebel, Buttrick, Poskin, Blom-Schieber, Hogan, McDonald. 2020. *Data-driven aerospace engineering: Reframing the industry with machine learning.* American Institute of Aeronautics and Astronautics Journal. 35 pages. DOI: https://doi.org/10.48550/arXiv.2008.10740. KDensity: 24.85. Refs: 169.

208. Li, Du, Zhou, Jing, Zhou, Zeng, Xiao, Zhu, Liu, Zhang. 2022. *ODE Transformer: An Ordinary Differential Equation-Inspired Model for Sequence Generation.* Annual Meeting of the Association for Computational Linguistics. 17 pages. DOI: https://doi.org/10.18653/v1/2022.acl-long.571. KDensity: 24.71. Repo. Refs: 67.

209. Rosofsky. 2021. *Physics Informed Deep Learning.* UIUC Department of Physics. NCSA Gravity group. HAL Training Series. 19 pages. DOI: NA. KDensity: 24.69. Repo. Refs: 24.

210. Chung, Mai. 2020. *Neural Ordinary Differential Equations Network and its Extensions.* Hoa Lac campus - FPT University. 40 pages. DOI: NA. KDensity: 24.52. Refs: 33.

211. Mohan1, Chattopadhyay, Miller. 2024. *What You See is Not What You Get: Neural Partial Differential Equations and The Illusion of Learning.* Los Alamos National Laboratory Unlimited Release LA-UR-24-32422. 29 pages. DOI: https://doi.org/10.48550/arXiv.2411.15101. KDensity: 24.52. Refs: 53.

212. Quarteroni, Gervasio, Regazzon. 2025. *Combining physics–based and data–driven models: advancing the frontiers of research with Scientific Machine Learning.* 127 pages. Published in Mathematical Models and Methods in Applied Sciences (2025). 127 pages. DOI: https://doi.org/10.1142/S0218202525500125. KDensity: 24.49. Refs: 267.

213. Baty. 2024. *A hands-on introduction to Physics-Informed Neural Networks for solving partial differential equations with benchmark tests taken from astrophysics and plasma physics.* 38 pages. DOI: https://doi.org/10.48550/arXiv.2403.00599. KDensity: 24.42. Repo. Refs: 22.

214. Hagge, Stinis, Yeung, Tartakovsky. 2017. *Solving differential equations with unknown constitutive relations as recurrent neural networks.* arxiv [Submitted on 6 Oct 2017]. 16 pages.

DOI: https://arxiv.org/abs/1710.02242v1. KDensity: 24.39. Refs: 12.

215. Zhang, Lu, Guo, Karniadakis. 2019. *Quantifying total uncertainty in physics-informed neural networks for solving forward and inverse stochastic problems.* Journal of Computational Physics. Volume. 34 pages. DOI: https://doi.org/10.1016/j.jcp.2019.07.048. KDensity: 24.24. Refs: 51.

216. Ramabathiran, Ramachandran. 2021. *SPINN: Sparse, Physics-based, and partially Interpretable Neural Networks for PDEs.* Journal of Computational Physics, Volume. 58 pages. DOI: https://doi.org/10.48550/arXiv.2102.13037. KDensity: 24.04. Repo. Refs: 45.

217. Perkins, Jaeger, Reinitz, Glass. 2006. *Reverse Engineering the Gap Gene Network of Drosophila melanogaster.* PLoS Comput Biol 2(5): e51.. 12 pages. DOI: https://doi.org/10.1371/journal.pcbi.0020051. KDensity: 24.01. Refs: 54.

218. Bradbury, Frostig, Hawkins, Johnson, Leary, Maclaurin, Necula, Paszke, VanderPlas, Milne, Zhang. 2018. *JAX: composable transformations of Python+NumPy programs.* 100 pages. URL: https://github.com/jax-ml. KDensity: 24. Refs: 0.

219. Nwankpa, Ijomah, Gachagan, Marshall. 2018. *Activation Functions: Comparison of trends in Practice and Research for Deep Learning.* 20 pages. DOI: https://doi.org/10.48550/arXiv.1811.03378. KDensity: 23.95. Refs: 82.

220. Raissi. 2018. *Forward-Backward Stochastic Neural Networks: Deep Learning of High-dimensional Partial Differential Equations.* arxiv [Submitted on 19 Apr 2018]. 17 pages. DOI: https://arxiv.org/abs/1804.07010v1. KDensity: 23.77. Refs: 24.

221. Berman, Buczak, Chavis, Corbett. 2019. *A Survey of Deep Learning Methods for Cyber Security.* Machine Learning for Cyber-Security. 35 pages. DOI: https://doi.org/10.3390/info10040122. KDensity: 23.75. Refs: 174.

222. Pun, Batra, Ramprasad, Mishin. 2019. *Physically informed artificial neural networks for atomistic modeling of materials.* Nature Communications volume 10, Article number: 2339 (2019). 10 pages. DOI: https://doi.org/10.1038/s41467-019-10343-5. KDensity: 23.7. Refs: 70.

223. He, Barajas-Solano, Tartakovsky, Tartakovsky. 2020. *Physics-informed neural networks for multiphysics data assimilation with application to subsurface transport.* Advances in Water Resources. Volume 141, July. 38 pages. DOI: https://doi.org/10.1016/j.advwatres.2020.103610. KDensity: 23.61. Refs: 39.

224. Schiassi, Furfaro, Leake, Florio, Johnston, Mortari. 2021. *Extreme theory of functional connections: A fast physics-informed neural network method for solving ordinary and partial differential equations.* Neurocomputing. Volume. 29 pages. DOI: https://doi.org/10.1016/j.neucom.2021.06.015. KDensity: 23.61. Refs: 40.

225. Dissanayake, Phan-Thien. 1994. *Neural-network-based approximations for solving partial differential equations.* Commun. Numer. Meth. Engng., 10: 195-201. 7 pages. DOI: https://doi.org/10.1002/cnm.1640100303. KDensity: 23.57. Refs: 5.

226. Grathwohl, Chen, Bettencourt, Sutskever, Duvenaud. 2019. *FFJORD: Free-form Continuous Dynamics for Scalable Reversible Generative Models.* 13 pages. DOI: https://doi.org/10.48550/arXiv.1810.01367. KDensity: 23.31. Refs: 23.

227. Lee, Bahri, Novak, Schoenholz, Pennington, Sohl-Dickstein. 2017. *Deep Neural Networks as Gaussian Processes.* NA. 17 pages. DOI: https://arxiv.org/abs/1711.00165v3. KDensity: 23.3. Refs: 29.

228. Mattheakis, Protopapas, Sondak, Giovanni, Kaxiras. 2019. *Physical Symmetries Embedded in Neural Networks.* 16 pages. DOI: https://arxiv.org/abs/1904.08991v3. KDensity: 23.25. Refs: 22.

229. Fabiani, Vandecasteele, Goswami, Siettos, Kevrekidis. 2025. *Enabling Local Neural Operators to perform Equation-Free System-Level Analysis.* Machine Learning (cs.LG); Dynamical Systems (math.DS); Numerical Analysis (math.NA); Machine Learning (stat.ML). 33 pages. DOI: https://doi.org/10.48550/arXiv.2505.02308. KDensity: 23.18. Refs: 73.

230. Paszke, Gross, Massa, Lerer, Bradbury, Chanan, Killeen, Lin, Gimelshein, Antiga, Desmaison, Kopf, Yang, DeVito, Raison, Tejani, Chilamkurthy, Steiner, Fang, Bai, Chintala. 2019. *PyTorch: An Imperative Style, High-Performance Deep Learning Library.* Advances in Neural Information Processing Systems 32 (NeurIPS 2019). 12 pages. DOI: https://arxiv.org/

abs/1912.01703v1. KDensity: 23.17. Refs: 44.

231. Gao, Wang. 2021. *A Bi-fidelity ensemble kalman method for PDE-constrained inverse problems in computational mechanics.* Comput Mech. 17 pages. DOI: https://doi.org/10.1007/s00466-021-01979-6. KDensity: 23.11. Refs: 57.

232. Kurth, Treichler, Romero, Mudigonda, Luehr, Phillips. 2018. *Exascale Deep Learning for Climate Analytics.* International Conference for High Performance Computing, Networking, Storage and Analysis. 12 pages. DOI: https://doi.org/10.1109/SC.2018.00054. KDensity: 23.08. Refs: 35.

233. Choi, Bahadori, Schuetz, Stewart, Sun. 2016. *Doctor AI: Predicting Clinical Events via Recurrent Neural Networks.* Proceedings of the 1st Machine Learning for Healthcare Conference, PMLR 56:301-318, 2016.. 18 pages. DOI: https://doi.org/10.48550/arXiv.1511.05942. KDensity: 23.05. Repo. Refs: 51.

234. Fan, Wang. 2023. *Differentiable hybrid neural modeling for fluid-structure interaction.* Journal of Computational Physics. 42 pages. DOI: https://doi.org/10.1016/j.jcp.2023.112584. KDensity: 23.05. Refs: 63.

235. Jin, Cai, Li, Karniadakis. 2021. *NSFnets (Navier-Stokes flow nets): Physics-informed neural networks for the incompressible Navier-Stokes equations.* Journal ofComputational Physics. 26 pages. DOI: https://doi.org/10.1016/j.jcp.2020.109951. KDensity: 22.92. Refs: 38.

236. Du, Dai, Trivedi, Upadhyay, Gomez-Rodriguez, Song. 2016. *Recurrent marked temporal point processes: Embedding event history to vector.* Association for Computing Machinery. 10 pages. DOI: https://doi.org/10.1145/2939672.2939875. KDensity: 22.9. Refs: 40.

237. Klooster. 2021. *Approximating differential equations using neural ODEs.* U of Twenhte. Department of Applied Mathematics. Faculty of Electrical Engineering. 22 pages. DOI: NA. KDensity: 22.77. Refs: 21.

238. Beidokhti, Malek. 2009. *Solving initial-boundary value problems for systems of partial differential equations using neural networks and optimization techniques.* Journal of the Franklin Institute. Volume 346, Issue 9, November 2009, Pages 898-913. 16 pages. DOI:

https://doi.org/10.1016/j.jfranklin.2009.05.003. KDensity: 22.68. Refs: 51.

239. Wiewel, Becher, Thuerey. 2018. *Latent-space Physics: Towards Learning the Temporal Evolution of Fluid Flow*. 16 pages. DOI: https://doi.org/10.48550/arXiv.1802.10123. KDensity: 22.57. Refs: 55.

240. He, Zhao, Chu. 2019. *AutoML: A Survey of the State-of-the-Art*. Elsevier Knowledge-Based Systems. Volume. 37 pages. DOI: https://doi.org/10.1016/j.knosys.2020.106622. KDensity: 22.51. Refs: 312.

241. Berg, Nyström. 2019. *Data-driven discovery of PDEs in complex datasets*. Journal of Computational Physics. Volume. 22 pages. DOI: https://doi.org/10.1016/j.jcp.2019.01.036. KDensity: 22.5. Refs: 38.

242. Baty, Baty. 2023. *Solving differential equations using physics informed deep learning: a hand-on tutorial with benchmark tests*. 23 pages. DOI: https://doi.org/10.48550/arXiv.2302.12260. KDensity: 22.49. Repo. Refs: 7.

243. Glorot, Bengio. 2010. *Understanding the difficulty of training deep feedforward neural networks*. International Conference on Artificial Intelligence and Statistics 2010. 8 pages. DOI: NA. KDensity: 22.38. Refs: 20.

244. Darbon, Langlois, Meng. 2019. *Overcoming the curse of dimensionality for some Hamilton-Jacobi partial differential equations via neural network architectures*. 44 pages. DOI: https://doi.org/10.48550/arXiv.1910.09045. KDensity: 22.36. Refs: 149.

245. Laubscher. 2021. *Simulation of multi-species flow and heat transfer using physics-informed neural networks*. Physics of Fluids - POF21-AR-02440.. 25 pages. DOI: https://doi.org/10.1063/5.0058529. KDensity: 22.36. Refs: 28.

246. Bonate. 2011. *Pharmacokinetic-pharmacodynamic modeling and simulation*. Bonate PL (2011) . Springer New York, NY. 30 pages. DOI: NA. KDensity: 22.33. Refs: 0.

247. Lu, Jin, Karniadakis. 2020. *DeepONet: Learning nonlinear operators for identifying differential equations based on the universal approximation theorem of operators*. 22 pages. DOI: https://doi.org/10.48550/arXiv.1910.03193. KDensity: 22.32. Repo. Refs: 34.

248. Yang, Perdikaris. 2019. *Adversarial Uncertainty Quantification in Physics-Informed Neural Networks.* Journal of Computational Physics. 33 pages, 7 figures. 33 pages. DOI: https://doi.org/10.1016/j.jcp.2019.05.027. KDensity: 22.27. Repo. Refs: 58.

249. Pfaff, Fortunato, Sanchez-Gonzalez, Battaglia. 2020. *Learning Mesh-Based Simulation with Graph Networks.* International Conference on Learning Representations (ICLR), 2021. 18 pages. DOI: https://arxiv.org/abs/2010.03409v4. KDensity: 22. Repo. Refs: 49.

250. Sompolinsky. 1988. *Statistical Mechanics of Neural Networks.* Physics Today 41 (12), 70–80 (1988). 11 pages. DOI: https://doi.org/10.1063/1.881142. KDensity: 21.91. Refs: 21.

251. Wight, Zhao. 2020. *Solving Allen-Cahn and Cahn-Hilliard Equations using the Adaptive Physics Informed Neural Networks.* math> arXiv:2007.04542. 25 pages. DOI: https://arxiv.org/abs/2007.04542v1. KDensity: 21.72. Refs: 31.

252. Zhang, Cheng, Gnanaskandan, Jagtap. 2025. *BubbleONet— A Physics-Informed Neural Operator for High-Frequency Bubble Dynamics.* Machine Learning (cs.LG). 35 pages. DOI: https://doi.org/10.48550/arXiv.2508.03965. KDensity: 21.66. Refs: 56.

253. Ramachandran, Zoph, Le. 2017. *Searching for Activation Functions.* 13 pages. DOI: https://doi.org/10.48550/arXiv.1710.05941. KDensity: 21.62. Refs: 53.

254. Akhare, Luo, Wang. 2022. *Physics-integrated Neural Differentiable (PiNDiff) Model for Composites Manufacturing.* Computer Methods in Applied Mechanics and Engineering.. 44 pages. DOI: https://doi.org/10.1016/j.cma.2023.115902. KDensity: 21.59. Refs: 63.

255. Özbay, Hamzehloo, Laizet, Tzirakis, Rizos, Schuller. 2021. *Poisson CNN: Convolutional neural networks for the solution of the Poisson equation on a Cartesian mesh.* Data-Centric Engineering. 2021;2:e6.. 31 pages. DOI: https://doi.org/10.1017/dce.2021.7. KDensity: 21.45. Repo. Refs: 40.

256. Sutskever, Vinyals, Le. 2014. *Sequence to Sequence Learning with Neural Networks.* NIPS'14: Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2. Pages 3104 - 3112. 9 pages. DOI: https://doi.org/10.48550/arXiv.1409.3215. KDensity: 21.44. Refs: 31.

257. Kalinin, Ziatdinov, Sumpter, White. 2022. *Physics is the New Data.* Data Analysis, Statistics and Probability (physics.data-an). 7 pages. DOI: https://doi.org/10.48550/arXiv.2204.05095. KDensity: 21.43. Refs: 27.

258. Liao, Poggio. 2016. *Bridging the Gaps Between Residual Learning, Recurrent Neural Networks and Visual Cortex.* 14 pages. DOI: https://doi.org/10.48550/arXiv.1604.03640. KDensity: 21.43. Refs: 39.

259. Baymani, Kerayechian, Effati. 2010. *Artificial neural networks approach for solving stokes problem.* Applied Mathematics, Vol.1 No.4, 2010. 5 pages. DOI: http://dx.doi.org/10.4236/am.2010.14037. KDensity: 21.4. Refs: 8.

260. Kakka. 2022. *Sequence to sequence AE-ConvLSTM network for modelling the dynamics of PDE systems.* 27 pages. DOI: https://doi.org/10.48550/arXiv.2208.07315. KDensity: 21.11. Repo. Refs: 19.

261. McGreivy, Hakim. 2024. *Weak baselines and reporting biases lead to overoptimism in machine learning for fluid-related partial differential equations.* Nature Machine Intelligence volume 6, pages 1256–1269 (2024). 47 pages. DOI: https://doi.org/10.1038/s42256-024-00897-5. KDensity: 21.08. Refs: 185.

262. Brunton, Proctor, Kutz. 2016. *Discovering governing equations from data by sparse identification of nonlinear dynamical systems.* Proc. Natl. Acad. Sci. U.S.A.113 (15) 3932-3937,. 20 pages. DOI: https://doi.org/10.1073/pnas.1517384113. KDensity: 21.03. Refs: 45.

263. Guo, Agarwal, Cooper, Tian, Gao, Guo, Guo. 2022. *Machine Learning for Metal Additive Manufacturing:Towards a Physics-Informed Data-Driven Paradigm.* Journal of Manufacturing Systems. Volume 62, January 2022, Pages 145-163. 40 pages. DOI: https://doi.org/10.1016/j.jmsy.2021.11.003. KDensity: 21.01. Refs: 193.

264. Pakravan, Mistani, Aragon-Calvo, Gibou. 2020. *Solving inverse-PDE problems with physics-aware neural networks.* 39 pages. DOI: https://arxiv.org/abs/2001.03608v3. KDensity: 20.9. Refs: 91.

265. Loiseau, Brunton. 2018. *Constrained sparse Galerkin regression.* J. Fluid Mech.. 27 pages.

DOI: https://doi.org/10.1017/jfm.2017.823. KDensity: 20.86. Repo. Refs: 65.

266. Li, Kovachki, Azizzadenesheli, Liu, Bhattacharya, Stuart, Anandkumar. 2020. *Neural Operator: Graph Kernel Network for Partial Differential Equations.* 21 pages. DOI: https://doi.org/10.48550/arXiv.2003.03485. KDensity: 20.82. Repo. Refs: 41.

267. Wang, Perdikaris. 2021. *Deep learning of free boundary and Stefan problems.* Journal of Computational Physics. Volume. 27 pages. DOI: https://doi.org/10.1016/j.jcp.2020.109914. KDensity: 20.81. Repo. Refs: 71.

268. Tartakovsky, Marrero, Perdikaris, Tartakovsky, Barajas-Solano. 2018. *Learning Parameters and Constitutive Relationships with Physics Informed Deep Neural Networks.* math> arXiv:1808.03398. 22 pages. DOI: https://arxiv.org/abs/1808.03398v2. KDensity: 20.78. Refs: 28.

269. Jordan, Mitchell. 2015. *Machine learning: Trends, perspectives, and prospects.* Science, 349(6245):255–260, 2015. 7 pages. DOI: https://doi.org/10.1126/science.aaa8415. KDensity: 20.72. Refs: 31.

270. Xie, Franz, Chu, Thuerey. 2018. *tempoGAN: A Temporally Coherent, Volumetric GAN for Super-resolution Fluid Flow.* ACM Transactions on Graphics (SIGGRAPH). 2018; 37(4): 1-15.; arXiv pre-print 1801.09710.. 15 pages. DOI: https://doi.org/10.1145/3072959.3073643. KDensity: 20.47. Repo. Refs: 60.

271. Morrill, Salvi, Kidger, Foster, Lyons. 2021. *Neural Rough Differential Equations for Long Time Series.* Proceedings of the Thirty-Second AAAI Conference on Artificial Intelligence, (AAAI-18), the 30th innovative Applications of Artificial Intelligence (IAAI-18), and the 8th AAAI Symposium on Educational Advances in Artificial Intelligence (EAAI-18), New Orleans, Louisiana, USA, February 2-7, 2018, pages 2811–2818. AAAI Press.. 22 pages. DOI: https://doi.org/10.48550/arXiv.2009.08295. KDensity: 20.41. Repo. Refs: 37.

272. Hackenberg, Grodd, Kreutz, Fischer, Esins, Grabenhenrich, Karagiannidis, Binder. 2021. *Using differentiable programming for flexible statistical modeling.* TheAmerican Statistician (2021) 1–10. 25 pages. DOI: https://doi.org/10.1080/00031305.2021.2002189. KDensity: 20.4. Repo. Refs: 37.

273. Meng, Karniadakis. 2020. *A composite neural network that learns from multi-fidelity data: Application to function approximation and inverse PDE problems.* Journal of Computational Physics. Volume. 29 pages. DOI: https://doi.org/10.1016/j.jcp.2019.109020. KDensity: 20.31. Refs: 37.

274. Bram, Parrott, Hutchinson, Steiert. 2022. *Introduction of an artificial neural network-based method for concentration-time predictions.* (2022) CPT Pharmacometrics Syst Pharmacol11:745–754. https://doi.org/10.1002/psp4.12786. 10 pages. DOI: https://doi.org/10.1002/psp4.12786. KDensity: 20.3. Refs: 21.

275. Pang, D'Elia, Parks, Karniadakis. 2020. *nPINNs: nonlocal Physics-Informed Neural Networks for a parametrized nonlocal universal Laplacian operator. Algorithms and Applications.* Journal of Computational Physics. 31 pages. DOI: https://doi.org/10.1016/j.jcp.2020.109760. KDensity: 20.23. Refs: 38.

276. Goswami, Yin, Yu, Karniadakis. 2021. *A physics-informed variational DeepONet for predicting the crack path in brittle materials.* Computer Methods in Applied Mechanics and Engineering. Volume. 39 pages. DOI: https://doi.org/10.1016/j.cma.2022.114587. KDensity: 20.1. Refs: 53.

277. He, Zhang, Ren, Sun. 2015. *Deep Residual Learning for Image Recognition.* Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.. 12 pages. DOI: https://doi.org/10.48550/arXiv.1512.03385. KDensity: 20. Refs: 50.

278. Milano, Koumoutsakos. 2002. *Neural Network Modeling for Near Wall Turbulent Flow.* Journal of Computational Physics. Volume 182, Issue. 26 pages. DOI: https://doi.org/10.1006/jcph.2002.7146. KDensity: 20. Refs: 28.

279. Lukosevicius, Jaeger. 2009. *Reservoir computing approaches to recurrent neural network training.* Computer Science Review. Volume 3, Issue 3, August 2009, Pages 127-149. 23 pages. DOI: https://doi.org/10.1016/j.cosrev.2009.03.005. KDensity: 19.96. Refs: 149.

280. Dwivedi, Srinivasan. 2019. *Physics Informed Extreme Learning Machine (PIELM)–A rapid method for the numerical solution of partial differential equations.* Neurocomputing. Volume. 29 pages. DOI: https://doi.org/10.1016/j.neucom.2019.12.099. KDensity: 19.93. Refs:

23.

281. Lew, Shah, Pati, Cattell, Zhang, Sandhupatla, Ng, Goli, Sinclair, Rogers, Aamodt. 2018. *Analyzing Machine Learning Workloads Using a Detailed GPU Simulator.* 2019 IEEE International Symposium on Performance Analysis of Systems and Software (ISPASS). 11 pages. DOI: http://dx.doi.org/10.48550/arXiv.1811.08933. KDensity: 19.9. Repo. Refs: 19.

282. Iten, Metger, Wilming, Rio, Renner. 2020. *Discovering Physical Concepts with Neural Networks.* Phys. Rev. Lett.. 18 pages. DOI: https://doi.org/10.1103/PhysRevLett.124.010508. KDensity: 19.83. Repo. Refs: 93.

283. Gomez, Ren, Urtasun, Grosse. 2017. *The Reversible Residual Network: Backpropagation Without Storing Activations.* Computer Vision and Pattern Recognition. 11 pages. DOI: https://doi.org/10.48550/arXiv.1707.04585. KDensity: 19.64. Repo. Refs: 37.

284. Sun, Han, Gao, Wang, Liu. 2023. *Unifying Predictions of Deterministic and Stochastic Physics in Mesh-reduced Space with Sequential Flow Generative Model.* 32nd Conference on Neural Information Processing Systems (NeurIPS 2018), Montréal, Canada.. 25 pages. DOI: NA. KDensity: 19.52. Refs: 54.

285. Gardner, Pleiss, Weinberger, Bindel, Wilson. 2018. *GPyTorch: Blackbox Matrix-Matrix Gaussian Process Inference with GPU Acceleration.* Advances in Neural Information Processing Systems 31 (NeurIPS 2018). 11 pages. DOI: https://arxiv.org/abs/1809.11165v6. KDensity: 19.27. Refs: 53.

286. He, Tran, Bortz, Choi. 2025. *Physics-informed active learning with simultaneous weak-form latent space dynamics identification.* International Journal for Numerical Methods in Engineering 126, no. 1 (2025): e7634. 31 pages. DOI: https://doi.org/10.48550/arXiv.2407.00337. KDensity: 19.12. Refs: 62.

287. Raissi, Yazdani, Karniadakis. 2020. *Hidden fluid mechanics: Learning velocity and pressure fields from flow visualizations.* Science 367(6481), 1026–1030 (2020). 9 pages. DOI: https://doi.org/10.1126/science.aaw4741. KDensity: 19.12. Repo. Refs: 19.

288. Kim, Choi, Widemann, Zohdi. 2022. *A fast and accurate physics-informed neural network reduced order model with shallow masked autoencoder.* Journal of Computational Physics, Journal Name: Journal of Computational Physics Vol. 451; ISSN 0021-9991. 35 pages. DOI: https://doi.org/10.1016/j.jcp.2021.110841. KDensity: 19. Refs: 77.

289. Alipanahi, Delong, Weirauch, Frey. 2015. *Predicting the sequence specificities of DNA- and RNA-binding proteins by deep learning.* Nature biotechnology 33 (2015) 831–838.. 10 pages. DOI: https://doi.org/10.1038/nbt.3300. KDensity: 18.98. Repo. Refs: 51.

290. Gao, Sun, Wang. 2021. *PhyGeoNet: Physics-informed geometry-adaptive convolutional neural networks for solving parameterized steady-state PDEs on irregular domain.* Journal of Computational Physics. Volume. 57 pages. DOI: https://doi.org/10.1016/j.jcp.2020.110079. KDensity: 18.95. Repo. Refs: 94.

291. Zobeiry, Humfeld. 2021. *A physics-informed machine learning approach for solving heat transfer equation in advanced manufacturing and engineering applications.* Engineering Applications of Artificial Intelligence. Volume 101, May. 27 pages. DOI: https://doi.org/10.1016/j.engappai.2021.104232. KDensity: 18.89. Refs: 24.

292. Rasmussen, Ghahramani. 2001. *Occam's Razor.* Part of Advances in Neural Information Processing Systems 13 (NIPS 2000). 7 pages. DOI: NA. KDensity: 18.86. Refs: 5.

293. Weinan. 2017. *A Proposal on Machine Learning via Dynamical Systems.* Commun. Math. Stat.. 13 pages. DOI: https://doi.org/10.1007/s40304-017-0103-z. KDensity: 18.84. Refs: 16.

294. Kollmannsberger, D'Angella, Jokeit, Herrmann. 2021. *Physics-informed neural networks for high-speed flows.* Computational Mechanics. Studies in Computational Intelligence, Springer International Publishing, Cham, p 55–84. 108 pages. DOI: https://doi.org/10.1007/978-3-030-76587-3_5. KDensity: 18.67. Repo. Refs: 92.

295. Raissi, Wang, Triantafyllou, Karniadakis. 2019. *Deep learning of vortex-induced vibrations.* Journal of Fluid Mechanics. 29 pages. DOI: https://doi.org/10.1017/jfm.2018.872. KDensity: 18.57. Repo. Refs: 51.

296. Sun, Gao, Pan, Wang. 2020. *Surrogate modeling for fluid flows based on physics-*

constrained deep learning without simulation data. Computer Methods in Applied Mechanics and Engineering. Volume. 43 pages. DOI: https://doi.org/10.1016/j.cma.2019.112732. KDensity: 18.47. Repo. Refs: 77.

297. Samaniego, Anitescu, Goswami, Nguyen-Thanh, Guo, Hamdia, Zhuang, Rabczuk. 2020. *An energy approach to the solution of partial differential equations in computational mechanics via machine learning: Concepts, Implementation and Applications.* Computer Methods in Applied Mechanics and Engineering. Volume. 37 pages. DOI: http://dx.doi.org/10.1016/j.cma.2019.112790. KDensity: 18.41. Repo. Refs: 29.

298. Saxe, McClelland, Ganguli. 2013. *Exact solutions to the nonlinear dynamics of learning in deep linear neural networks.* International Conference on Learning Representations 2014. 22 pages. DOI: https://doi.org/10.48550/arXiv.1312.6120. KDensity: 18.08. Refs: 25.

299. Subramani, Vadivelu, Kamath. 2020. *Enabling Fast Differentially Private SGD via Just-in-Time Compilation and Vectorization.* arxiv [Submitted on 18 Oct 2020 (v1), last revised 26 Oct 2021 (this version, v2)]. 30 pages. DOI: https://arxiv.org/abs/2010.09063v2. KDensity: 18.07. Refs: 71.

300. Raissi, Babaee, Givi. 2019. *Deep Learning of Turbulent Scalar Mixing.* Phys. Rev. Fluids. 19 pages. DOI: https://doi.org/10.1103/PhysRevFluids.4.124501. KDensity: 18.01. Refs: 69.

301. Patel, Manickam, Trask, Wood, Lee, Tomas, Cyr. 2020. *Thermodynamically consistent physics-informed neural networks for hyperbolic systems.* eprint arXiv:2012.05343. 36 pages. DOI: https://ui.adsabs.harvard.edu/link_gateway/2020arXiv201205343P/doi:10.48550/arXiv.2012.05343. KDensity: 17.9. Refs: 80.

302. Lutter, Ritter, Peters. 2019. *Deep Lagrangian Networks: Using Physics as Model Prior for Deep Learning.* Published at ICLR 2019. 17 pages. DOI: https://doi.org/10.48550/arXiv.1907.04490. KDensity: 17.83. Repo. Refs: 47.

303. Haber, Ruthotto. 2017. *Stable Architectures for Deep Neural Networks Inverse Problems.* Volume 34, Number 1 Inverse Problems, Volume 34, Number. 23 pages. DOI: https://doi.org/10.48550/arXiv.1705.03341. KDensity: 17.75. Refs: 48.

304. Huang, Xu, Farhat, Darve. 2020. *Learning Constitutive Relations from Indirect Observations Using Deep Neural Networks.* Journal of Computational Physics. Volume. 40 pages. DOI: https://www.sciencedirect.com/science/article/abs/pii/S0021999120302655?via%3Dihub. KDensity: 17.73. Repo. Refs: 66.

305. Xu, Li, Darve, Harris. 2019. *Learning Hidden Dynamics using Intelligent Automatic Differentiation.* 25 pages. DOI: https://doi.org/10.48550/arXiv.1912.07547. KDensity: 17.72. Repo. Refs: 34.

306. Baldillou. 2024. *An introduction to neural ordinary differential equations.* U of Barcelona. 73 pages. DOI: NA. KDensity: 17.63. Repo. Refs: 34.

307. Geneva, Zabaras. 2020. *Transformers for Modeling Physical Systems.* Neural Networks; Volume 146, February 2022, Pages 272-289. 39 pages. DOI: https://ui.adsabs.harvard.edu/link_gateway/2020arXiv201003957G/doi:10.48550/arXiv.2010.03957. KDensity: 17.45. Refs: 73.

308. Raissi, Karniadakis. 2018. *Hidden physics models: Machine learning of nonlinear partial differential equations.* Journal of Computational Physics 357(4). 31 pages. DOI: https://www.sciencedirect.com/science/article/abs/pii/S0021999117309014?via%3Dihub. KDensity: 17.37. Repo. Refs: 41.

309. Lake, Salakhutdinov, Tenenbaum. 2015. *Human-level concept learning through probabilistic program induction.* Science 350 (2015)1332–1338.. 8 pages. DOI: https://doi.org/10.1126/science.aab3050. KDensity: 17.26. Repo. Refs: 62.

310. Blundell, Cornebise, Kavukcuoglu, Wierstra. 2015. *Weight Uncertainty in Neural Networks.* In Proceedings of the 32nd International Conference on Machine Learning (ICML 2015). 10 pages. DOI: https://arxiv.org/abs/1505.05424v2. KDensity: 17.2. Refs: 43.

311. Meibohm, Derendorf. 1997. *Basic concepts of pharmacokinetic/pharmacodynamic (PK/PD) modelling.* Int J Clin Pharmacol Ther. 1997 Oct;35(10):401-13.. 13 pages. DOI: NA. KDensity: 17.15. Refs: 41.

312. Mao, Jagtap, Karniadakis. 2020. *Physics-informed neural networks for high-speed flows.*

Computer Methods in AppliedMechanics and Engineering. 38 pages. DOI: https://doi.org/10.1016/j.cma.2019.112789. KDensity: 17.11. Refs: 50.

313. Mariappan, Nath, Karniadakis. 2024. *Learning thermoacoustic interactions in combustors using a physics-informed neural network.* Engineering Applications of Artificial Intelligence. Volume 138, Part B, December. 42 pages. DOI: https://doi.org/10.1016/j.engappai.2024.109388. KDensity: 17.1. Refs: 78.

314. Chiaramonte, Kiener. 2018. *Solving differential equations using neural networks.* Stanford. 5 pages. DOI: NA. KDensity: 17. Refs: 0.

315. Thompson, Connors, Zavala, Venturelli. 2025. *Physics-constrained neural ordinary differential equation models to discover and predict microbial community dynamics.* bioRxiv 2025.07.08.663743. 45 pages. DOI: https://doi.org/10.1101/2025.07.08.663743. KDensity: 16.93. Refs: 53.

316. Xu, Darve. 2019. *The Neural Network Approach to Inverse Problems in Differential Equations.* NA. 32 pages. DOI: https://doi.org/10.48550/arXiv.1901.07758. KDensity: 16.88. Refs: 54.

317. Kovachki, Li, Liu, Azizzadenesheli, Bhattacharya, Stuart, Anandkumar. 2021. *Neural Operator: Learning Maps Between Function Spaces.* Kovachki, N., Li, Z., Liu, B., Azizzadenesheli, K., Bhattacharya, K., Stuart, A., and Anandkumar, A.Neural operator: Learning maps between function spaces. arXiv preprint arXiv:2108.08481, 2021.. 97 pages. DOI: https://doi.org/10.48550/arXiv.2108.08481. KDensity: 16.75. Repo. Refs: 133.

318. Cao. 2021. *Choose a Transformer: Fourier or Galerkin.* Part of Advances in Neural Information Processing Systems 34 (NeurIPS 2021). 36 pages. DOI: NA. KDensity: 16.72. Repo. Refs: 100.

319. He, Choi, Fries, Belof, Chen. 2023. *gLaSDI: Parametric physics-informed greedy latent space dynamics identification.* Journal of Computational Physics. Volume. 53 pages. DOI: https://doi.org/10.1016/j.jcp.2023.112267. KDensity: 16.7. Refs: 102.

320. Raissi, Perdikaris, Karniadakis. 2017. *Inferring solutions of differential equations using*

noisy multi-fidelity data. Journal of Computational Physics. Volume. 11 pages. DOI: https://doi.org/10.1016/j.jcp.2017.01.060. KDensity: 16.63. Refs: 135.

321. Lin, Tegmark, Rolnick. 2017. *Why Does Deep and Cheap Learning Work So Well?*. J Stat Phys. 16 pages. DOI: https://doi.org/10.1007/s10955-017-1836-5. KDensity: 16.58. Refs: 50.

322. Graves. 2011. *Practical Variational Inference for Neural Networks*. Advances in Neural Information Processing Systems 24 (NIPS 2011). 9 pages. DOI: NA. KDensity: 16.56. Refs: 26.

323. Hensman, Lawrence. 2013. *Gaussian Processes for Big Data*. arxiv [Submitted on 26 Sep 2013]. 9 pages. DOI: https://arxiv.org/abs/1309.6835v1. KDensity: 16.56. Refs: 17.

324. Dwivedi, Srinivasan, Krishnamurthi. 2024. *Physics informed contour selection for rapid image segmentation*. Scientific Reports volume 14, Article number: 6996 (2024). 17 pages. DOI: https://doi.org/10.1038/s41598-024-57281-x. KDensity: 16.48. Refs: 26.

325. Jha. 2025. *From Theory to Application: A Practical Introduction to Neural Operators in Scientific Computing*. Computational Engineering, Finance, and Science (cs.CE); Machine Learning (cs.LG). 53 pages. DOI: https://doi.org/10.48550/arXiv.2503.05598. KDensity: 16.46. Refs: 40.

326. Errico. 1997. *What Is an Adjoint Model?*. Bulletin of the American Meteorological Society. Volume 78. Issue 11. 15 pages. DOI: https://doi.org/10.1175/1520-0477(1997)078%3C2577:WIAAM%3E2.0.CO;2. KDensity: 16.4. Refs: 55.

327. Hornik, Stinchcombe, White. 1989. *Multilayer feedforward networks are universal approximators*. Neural Networks. Volume 2, Issue. 8 pages. DOI: https://doi.org/10.1016/0893-6080(89)90020-8. KDensity: 16.38. Refs: 26.

328. Deighan, Actor, Patel. 2025. *Mixture of neural operator experts for learning boundary conditions and model selection*. https://doi.org/10.48550/arXiv.2502.04562. 25 pages. DOI: https://doi.org/10.48550/arXiv.2502.04562. KDensity: 16.36. Refs: 30.

329. Lipton, Kale, Elkan, Wetzel. 2017. *Learning to Diagnose with LSTM Recurrent Neural Net-*

works. International Conference on Learning Representations. 18 pages. DOI: https://doi.org/10.48550/arXiv.1511.03677. KDensity: 16.33. Refs: 54.

330. Yang, Zhang, Karniadakis. 2020. *Physics-Informed Generative Adversarial Networks for Stochastic Differential Equations.* 35 pages. DOI: https://doi.org/10.1137/18M1225409. KDensity: 16.28. Refs: 38.

331. Rackauckas, Ma, Martensen, Warner, Zubov, Supekar, Skinner, Ramadhan, Edelman. 2021. *Universal differential equations for scientific machine learning.* (2021) arXiv:200104385v4 [csLG]. https://doi.org/10.48550/arXiv.2001.04385. 55 pages. DOI: https://doi.org/10.48550/arXiv.2001.04385. KDensity: 16.27. Repo. Refs: 126.

332. Qiao, Liang, Koltun, Lin. 2020. *Scalable Differentiable Physics for Learning and Control.* ICML 20 Proceedings of the 37th International Conference on Machine Learning. Article No.: 727, Pages 7847 - 7856. 12 pages. DOI: https://doi.org/10.48550/arXiv.2007.02168. KDensity: 16.16. Repo. Refs: 30.

333. Falcon. 2019. *PyTorch Lightning.* GitHub. 1 pages. URL: https://github.com/Lightning-AI/pytorch-lightning. KDensity: 16. Refs: 0.

334. Lu, Dao, Kumar, Ramamurty, Karniadakis, Suresh. 2020. *Extraction of mechanical properties of materials through deep learning from instrumented indentation.* Proc. Natl. Acad. Sci. U.S.A.. 11 pages. DOI: https://doi.org/10.1073/pnas.1922210117. KDensity: 15.81. Repo. Refs: 50.

335. Gopalani, Karmakar, Kumar, Mukherjee. 2024. *Towards Size-Independent Generalization Bounds for Deep Operator Nets.* Transactions on Machine Learning Research. 33 pages. DOI: NA. KDensity: 15.78. Repo. Refs: 58.

336. Baydin, Pearlmutter, Radul, Siskind. 2018. *Automatic Differentiation in Machine Learning: A Survey.* Journal of Machine Learning Research. 43 pages. DOI: https://doi.org/10.48550/arXiv.1502.05767. KDensity: 15.77. Repo. Refs: 208.

337. Jin, Zhang, Zhu, Tang, Karniadakis. 2020. *SympNets: Intrinsic structure-preserving symplectic networks for identifying Hamiltonian systems.* cs> arXiv:2001.03750. 18 pages. DOI:

https://arxiv.org/abs/2001.03750v3. KDensity: 15.72. Refs: 53.

338. Petra, Petra, Zhang, Constantinescu, Anitescu. 2016. *A Bayesian Approach for Parameter Estimation With Uncertainty for Dynamic Power Systems.* IEEE Transactions on Power Systems (Volume: 32, Issue: 4, July 2017). 10 pages. DOI: https://doi.org/10.1109/TPWRS.2016.2625277. KDensity: 15.6. Repo. Refs: 40.

339. Perdikaris, Venturi, Karniadakis. 2016. *Multifidelity Information Fusion Algorithms for High-Dimensional Systems and Massive Data sets.* SIAM Journal on Scientific Computing. Vol. 38, Iss. 4 (2016)10.1137/15M1055164. 19 pages. DOI: https://doi.org/10.1137/15M1055164. KDensity: 15.58. Refs: 35.

340. Babuška, Suri. 1990. *The p- and h-p versions of the finite element method, an overview.* Computer Methods in Applied Mechanics and Engineering. Volume 80, Issues 1–3, June 1990, Pages 5-26. 22 pages. DOI: https://doi.org/10.1016/0045-7825(90)90011-A. KDensity: 15.41. Refs: 83.

341. Perdikaris, Raissi, Damianou, Lawrence, Karniadakis. 2017. *Nonlinear information fusion algorithms for data-efficient multi-fidelity modelling.* Proc. R. Soc. A.47320160751. 16 pages. DOI: https://doi.org/10.1098/rspa.2016.0751. KDensity: 15.32. Refs: 26.

342. Jasak1, Jemcov, Tukovi. 2007. *OpenFOAM: A C++ library for complex physics simulations.* In: International Workshop on Coupled Methods in Numerical Dynamics, vol. 1000, pp. 1–20. IUC Dubrovnik Croatia (2007). 20 pages. DOI: NA. KDensity: 15.3. Refs: 24.

343. Karalias, Loukas. 2020. *Erdos Goes Neural: an Unsupervised Learning Framework for Combinatorial Optimization on Graphs.* Advances on Neural Information Processing Systems, pp. 6659–6672. 21 pages. DOI: https://doi.org/10.48550/arXiv.2006.10643. KDensity: 15.24. Repo. Refs: 88.

344. Pestourie, Mroueh, Rackauckas, Johnson. 2023. *Physics-enhanced deep surrogates for partial differential equations.* Nature Machine Intelligence volume 5, pages 1458–1465 (2023). 40 pages. DOI: https://doi.org/10.1038/s42256-023-00761-y. KDensity: 15.23. Repo. Refs: 52.

345. Lagaris, Likas, Papageorgiou. 2000. *Neural-network methods for boundary value problems with irregular boundaries.* IEEE Trans Neural Netw. 2000;11(5):1041-9.. 9 pages. DOI: https://doi.org/10.1109/72.870037. KDensity: 15.21. Refs: 12.

346. Brunton. 2023. *Neural ODEs (NODEs) Physics Informed Machine Learning.* YouTube. 23 pages. URL: https://www.youtube.com/watch?v=nJphsM4obOk. KDensity: 15.17. Refs: 4.

347. Gao, Han, Fan, Sun, Liu, Duan, Wang. 2024. *Bayesian conditional diffusion models for versatile spatiotemporal turbulence generation.* Computer Methods in Applied Mechanics and Engineering. 37 pages. DOI: https://doi.org/10.1016/j.cma.2024.117023. KDensity: 15.16. Refs: 59.

348. Cheridito, Jentzen, Rossmannek. 2019. *Efficient approximation of high-dimensional functions with neural networks.* IEEE Trans. Neural Netw. Learn. Syst. (2021). 15 pages. DOI: https://arxiv.org/abs/1912.04310v3. KDensity: 15.13. Refs: 43.

349. Lin, Chen, Yan. 2013. *Network In Network.* 10 pages. DOI: https://doi.org/10.48550/arXiv.1312.4400. KDensity: 15.1. Refs: 20.

350. Hui, Chris, Carlos, Claes, Peter, S.. 2018. *Spectral/hp element methods: Recent developments, applications, and perspectives.* Volume 30, pages 1–22, (2018). 22 pages. DOI: https://doi.org/10.1007/s42241-018-0001-1. KDensity: 15. Refs: 144.

351. Li, Wong, Chen, Duvenaud. 2020. *Scalable Gradients for Stochastic Differential Equations.* AISTATS 2020. 25 pages. DOI: https://doi.org/10.48550/arXiv.2001.01328. KDensity: 14.96. Repo. Refs: 90.

352. Sun, Tao, Du. 2018. *Stochastic Training of Residual Networks: a Differential Equation Viewpoint.* 20 pages. DOI: https://arxiv.org/abs/1812.00174v1. KDensity: 14.95. Refs: 36.

353. Shahriari, Swersky, Wang, Adams, Freitas. 2016. *Taking the Human Out of the Loop: A Review of Bayesian Optimization.* 28 pages. DOI: https://doi.org/10.1109/JPROC.2015.2494218. KDensity: 14.83. Refs: 163.

354. Yang, Daskalakis, Karniadakis. 2020. *Generative Ensemble Regression: Learning Particle Dynamics from Observations of Ensembles with Physics-Informed Deep Generative Models.*

cs> arXiv:2008.01915. 35 pages. DOI: https://arxiv.org/abs/2008.01915v2. KDensity: 14.75. Refs: 32.

355. Jin, McCann, Froustey, Unser. 2017. *Deep Convolutional Neural Network for Inverse Problems in Imaging*. IEEE Transactions on Image Processing, vol. 26, no. 9, pp. 4509-4522, Sept. 2017. 14 pages. DOI: https://doi.org/10.1109/TIP.2017.2713099. KDensity: 14.65. Refs: 65.

356. Shwartz-Ziv, Tishby. 2017. *Opening the Black Box of Deep Neural Networks via Information*. 19 pages. DOI: https://doi.org/10.48550/arXiv.1703.00810. KDensity: 14.31. Refs: 22.

357. Luo, Yang. 2020. *Two-Layer Neural Networks for Partial Differential Equations: Optimization and Generalization Theory*. math> arXiv:2006.15733. 31 pages. DOI: https://arxiv.org/abs/2006.15733v2. KDensity: 14.28. Refs: 52.

358. Voleti. 2020. *A brief tutorial on Neural ODEs*. 51 pages. DOI: NA. KDensity: 14.25. Repo. Refs: 33.

359. Dai, Khalil, Zhang, Dilkina, Song. 2017. *Learning Combinatorial Optimization Algorithms over Graphs*. Advances on Neural Information Processing Systems, pp. 6351–6361, 2017. 24 pages. DOI: https://doi.org/10.48550/arXiv.1704.01665. KDensity: 14.04. Repo. Refs: 38.

360. Siegelmann, Sontag. 1992. *On the computational power of neural nets*. COLT '92: Proceedings of the fifth annual workshop on Computational learning theory. Pages 440 - 449. 10 pages. DOI: https://doi.org/10.1145/130385.130432. KDensity: 14. Refs: 21.

361. Hopfield. 1982. *Neural Networks and Physical Systems with Emergent Collective Computational Abilities*. Proceedings of the National Academy of Sciences. 5 pages. DOI: https://doi.org/10.1073/pnas.79.8.2554. KDensity: 14. Refs: 32.

362. Tariyal, Majumdar, Singh, Vatsa. 2016. *Greedy Deep Dictionary Learning*. 9 pages. DOI: https://arxiv.org/abs/1602.00203v1. KDensity: 13.99. Refs: 67.

363. Chang, Zhang, Han, Yu, Guo, Tan, Cui, Witbrock, Hasegawa-Johnson, Huang. 2017. *Di-*

lated Recurrent Neural Networks. Event 31st Annual Conference on Neural Information Processing Systems, NIPS 2017 - Long Beach, United States Duration: Dec 4 2017 → Dec 9 2017. 13 pages. DOI: https://doi.org/10.48550/arXiv.1710.02224. KDensity: 13.92. Repo. Refs: 30.

364. Gulian, Raissi, Perdikaris, Karniadakis. 2018. *Machine Learning of Space-Fractional Differential Equations*. Computer Science > Machine Learning. arXiv:1808.00931. 26 pages. DOI: https://arxiv.org/abs/1808.00931v3. KDensity: 13.89. Refs: 40.

365. Schmidt, Lipson. 2009. *Distilling Free-Form Natural Laws from Experimental Data*. Science Vol. 324, No. 5923. 6 pages. DOI: https://doi.org/10.1126/science.1165893. KDensity: 13.8. Refs: 25.

366. Lee, You. 2019. *Data-driven prediction of unsteady flow over a circular cylinder using deep learning*. Journal of Fluid Mechanics , Volume 879 , 25 November 2019 , pp. 217 - 254. 38 pages. DOI: https://doi.org/10.1017/jfm.2019.700. KDensity: 13.63. Refs: 39.

367. Raissi, Perdikaris, Karniadakis. 2017. *Machine learning of linear differential equations using Gaussian processes*. Journal ofComputational Physics. 18 pages. DOI: https://doi.org/10.1016/j.jcp.2017.07.050. KDensity: 13.61. Refs: 42.

368. Berg, Hasenclever, Tomczak, Welling. 2018. *Sylvester Normalizing Flows for Variational Inference*. arxiv [Submitted on 15 Mar 2018 (v1), last revised 20 Feb 2019 (this version, v2)]. 12 pages. DOI: https://arxiv.org/abs/1803.05649v2. KDensity: 13.59. Refs: 27.

369. Krizhevsky, Sutskever, Hinton. 2012. *ImageNet Classification with Deep Convolutional Neural Networks*. Advances in Neural Information Processing Systems. 9 pages. DOI: http://dx.doi.org/10.1145/3065386. KDensity: 13.45. Refs: 26.

370. Raissi, Yazdani, Karniadakis. 2018. *Hidden Fluid Mechanics: A Navier-Stokes Informed Deep Learning Framework for Assimilating Flow Visualization Data*. arxiv [Submitted on 13 Aug 2018]. 33 pages. DOI: https://arxiv.org/abs/1808.04327v1. KDensity: 13.42. Refs: 44.

371. Tartakovsky, Marrero, Perdikaris, Tartakovsky, Barajas-Solano. 2020. *Physics-Informed*

Deep Neural Networks for Learning Parameters and Constitutive Relationships in Subsurface Flow Problems. Water Resources Research. Volume 56. Issue number 5. 47 pages. DOI: https://doi.org/10.1029/2019WR026731. KDensity: 13.36. Refs: 43.

372. Majda, Harlim. 2012. *Physics constrained nonlinear regression models for time series.* Nonlinearity 26 201. 21 pages. DOI: http://10.1088/0951-7715/26/1/201. KDensity: 13.24. Refs: 39.

373. Patel, Trask, Wood, Cyr. 2020. *A physics-informed operator regression framework for extracting data-driven continuum models.* Computer Methods in Applied Mechanics and Engineering. Volume. 38 pages. DOI: https://doi.org/10.1016/j.cma.2020.113500. KDensity: 13.13. Repo. Refs: 60.

374. Cai, Kang, Wang. 2017. *A stochastic SIRS epidemic model with nonlinear incidence rate.* Applied Mathematics and Computation. Volume. 20 pages. DOI: https://doi.org/10.1016/j.amc.2017.02.003. KDensity: 12.95. Refs: 70.

375. Kidger. 2022. *On Neural Differential Equations.* University of Oxford. Mathematical Institute. 231 pages. DOI: https://doi.org/10.48550/arXiv.2202.02435. KDensity: 12.92. Repo. Refs: 291.

376. Rowley, Mezic, Bagheri, Schlatter, Henningson. 2009. *Spectral analysis of nonlinear flows.* J. Fluid Mech., 645:115–127, 2009.. 13 pages. DOI: https://doi.org/10.1017/S0022112009992059. KDensity: 12.91. Refs: 15.

377. Mezic. 2013. *Analysis of fluid flows via spectral properties of the koopman operator.* Annual Review of Fluid Mechanics, 45:357–378, 2013.. 24 pages. DOI: https://doi.org/10.1146/annurev-fluid-011212-140652. KDensity: 12.75. Refs: 49.

378. Zhu, Zabaras, Koutsourelakis, Perdikaris. 2019. *Physics-Constrained Deep Learning for High-dimensional Surrogate Modeling and Uncertainty Quantification without Labeled Data.* Journal of Computational Physics. Volume. 51 pages. DOI: https://doi.org/10.1016/j.jcp.2019.05.024. KDensity: 12.63. Repo. Refs: 92.

379. Mao, Lu, Marxen, Zaki, Karniadakis. 2020. *DeepM&Mnet for hypersonics: Predicting the*

coupled flow and finite-rate chemistry behind a normal shock using neural-network approximation of operators. Journal of Computational Physics. Volume. 37 pages. DOI: https://doi.org/10.1016/j.jcp.2021.110698. KDensity: 12.57. Refs: 55.

380. Basdevant, Deville, Haldenwang, Lacroix, Ouazzani, Peyret, Orlandi, Patera. 1986. *Spectral and finite difference solutions of the Burgers equation*. Computers & fluids 14 (1986) 23–41.. 19 pages. DOI: https://doi.org/10.1016/0045-7930(86)90036-8. KDensity: 12.47. Refs: 15.

381. Diaz, Choi, Heinkenschloss. 2023. *A fast and accurate domain-decomposition nonlinear manifold reduced order model*. Computer Methods in Applied Mechanics and Engineering, Volume. 41 pages. DOI: https://doi.org/10.48550/arXiv.2305.15163. KDensity: 12.46. Refs: 72.

382. Zhou. 2024. *Nonlocal Turbulence Models with neural networks*. Virginia Tech. 47 pages. DOI: NA. KDensity: 12.46. Refs: 4.

383. Chen, Duan, Karniadakis. 2019. *Learning and meta-learning of stochastic advection-diffusion-reaction systems from sparse measurements*. European Journal of Applied Mathematics. 31 pages. DOI: https://doi.org/10.48550/arXiv.1910.09098. KDensity: 12.32. Refs: 24.

384. McFall, Mahan. 2009. *Artificial Neural Network Method for Solution of Boundary Value Problems With Exact Satisfaction of Arbitrary Boundary Conditions*. IEEE Transactions on Neural Networks (Volume: 20, Issue: 8, August 2009). 13 pages. DOI: https://doi.org/10.1109/TNN.2009.2020735. KDensity: 12.31. Refs: 20.

385. Zubov, McCarthy, Ma, Calisto, Pagliarino, Azeglio, Bottero, Luján, Sulzer, Bharambe, Vinchhi, Balakrishnan, Upadhyay, Rackauckas. 2021. *NeuralPDE: Automating Physics-Informed Neural Networks (PINNs) with Error Approximations*. cs> arXiv:2107.09443. 77 pages. DOI: https://arxiv.org/abs/2107.09443v1. KDensity: 12.16. Repo. Refs: 60.

386. Lawrence. 2004. *Gaussian Process Latent Variable Models for Visualisation of High Dimensional Data*. Advances in Neural Information Processing Systems 16 (NIPS 2003). 8 pages. DOI: NA. KDensity: 12.13. Refs: 11.

387. Tang, Liu, Durlofsky. 2020. *A deep-learning-based surrogate model for data assimilation in dynamic subsurface flow problems.* 47 pages. DOI: https://doi.org/10.1016/j.jcp.2020.109456. KDensity: 12.01. Refs: 47.

388. Kalajahi, Csala, Mamun, Yadav, Amili, Arzani, D'Souza. 2024. *Input Parameterized Physics Informed Neural Network for Advanced 4D Flow MRI Processing.* Engineering Applications of Artificial Intelligence. Volume. 50 pages. DOI: https://doi.org/10.1016/j.engappai.2025.110600. KDensity: 12. Refs: 66.

389. Lee, Liu, Darbon, Karniadakis. 2024. *Automatic discovery of optimal meta-solvers via multi-objective optimization.* Numerical Analysis (math.NA); Optimization and Control (math.OC). 25 pages. DOI: https://doi.org/10.48550/arXiv.2412.00063. KDensity: 11.88. Refs: 5.

390. Franke, Schaback. 1998. *Solving partial differential equations by collocation using radial basis functions.* Applied Mathematics and Computation. Volume 93, Issue. 12 pages. DOI: https://doi.org/10.1016/S0096-3003(97)10104-7. KDensity: 11.75. Refs: 18.

391. Shi, Tsymbalov, Dao, Suresh, Shapeev, Li. 2019. *Deep elastic strain engineering of bandgap through machine learning.* Proc. Natl. Acad. Sci. U.S.A.. 6 pages. DOI: https://doi.org/10.1073/pnas.1818555116. KDensity: 11.66. Refs: 29.

392. Pang, Yang, Karniadakis. 2018. *Neural-net-induced Gaussian process regression for function approximation and PDE solution.* Journal of Computational Physics. Volume. 24 pages. DOI: https://doi.org/10.1016/j.jcp.2019.01.045. KDensity: 11.59. Repo. Refs: 24.

393. Hethcote. 2000. *The Mathematics of Infectious Diseases.* SIAM Review. Vol. 42, Iss. 4 (2000). 55 pages. DOI: https://doi.org/10.1137/S0036144500371907. KDensity: 11.58. Refs: 202.

394. Mhaskar, Poggio. 2019. *Function approximation by deep networks.* Communications in pure and applied mathematics. 9 pages. DOI: https://arxiv.org/abs/1905.12882v2. KDensity: 11.55. Refs: 22.

395. Zhang, Sandu. 2014. *FATODE: a library for forward, adjoint, and tangent linear integration*

of ODEs. SIAM Journal on Scientific ComputingVol. 36, Iss. 5 (2014). 30 pages. DOI: https://doi.org/10.1137/130912335. KDensity: 11.54. Refs: 28.

396. Rebai, Boukhris, Toujani, Gueddiche, Banna, Souissi, Lasram, Rayana, Zaag. 2023. *Unsupervised physics-informed neural network in reaction-diffusion biology models (Ulcerative colitis and Crohn's disease cases) A preliminary study*. cs>arXiv:2302.07405. 85 pages. DOI: https://doi.org/10.48550/arXiv.2302.07405. KDensity: 11.34. Refs: 56.

397. Lauzon, Cheung, Shin, Choi, Copeland, Huynh. 2024. *S-OPT: A Points Selection Algorithm for Hyper-Reduction in Reduced Order Models*. Numerical Analysis (math.NA); Computational Engineering, Finance, and Science (cs.CE). 26 pages. DOI: https://doi.org/10.48550/arXiv.2203.16494. KDensity: 11.31. Refs: 66.

398. Manohar, Brunton, Kutz, Brunton. 2018. *Data-driven sparse sensor placement for reconstruction: Demonstrating the benefits of exploiting known patterns*. IEEE Control Systems Magazine. Volume 38, Issue 3. 34 pages. DOI: https://doi.org/10.1109/MCS.2018.2810460. KDensity: 11.3. Repo. Refs: 149.

399. Luo, Kareem. 2020. *Bayesian deep learning with hierarchical prior: Predictions from limited and noisy data*. Structural Safety. Volume 84, May. 34 pages. DOI: https://doi.org/10.1016/j.strusafe.2019.101918. KDensity: 11.2. Refs: 41.

400. Li, Wang, Lee, Luo. 2022. *Physics-informed neural networks for solving multiscale mode-resolved phonon Boltzmann transport equation*. Materials Today Physics. 31 pages. DOI: https://doi.org/10.1016/j.mtphys.2021.100429. KDensity: 11.15. Repo. Refs: 63.

401. Wang, Wu, Ling, Iaccarino, Xiao. 2017. *A Comprehensive Physics-Informed Machine Learning Framework for Predictive Turbulence Modeling*. Physical Review Fluids.. 34 pages. DOI: https://arxiv.org/abs/1701.07102v2. KDensity: 11.09. Refs: 35.

402. Lanthaler, Mishra, Karniadakis. 2021. *Error estimates for DeepOnets: A deep learning framework in infinite dimensions*. math> arXiv:2102.09618. 123 pages. DOI: https://arxiv.org/abs/2102.09618v3. KDensity: 11.09. Refs: 67.

403. Schmid. 2010. *Dynamic mode decomposition of numerical and experimental data*. Journal

of Fluid Mechanics, 656:5–28, August 2010.. 25 pages. DOI: https://doi.org/10.1017/S0022112010001217. KDensity: 11. Refs: 30.

404. Raissi, Perdikaris, Karniadakis. 2017. *Numerical Gaussian Processes for Time-dependent and Non-linear Partial Differential Equations.* Methods and Algorithms for Scientific Computing. 51 pages. DOI: https://doi.org/10.1137/17M1120762. KDensity: 10.99. Refs: 37.

405. Duvenaud. 2018. *Neural Ordinary Differential Equations.* YouTube. 32 pages. URL: https://www.youtube.com/watch?v=V6nGT0Gakyg. KDensity: 10.97. Repo. Refs: 7.

406. BergKaj, Nyström. 2018. *A unified deep artificial neural network approach to partial differential equations in complex geometries.* Neurocomputing. Volume. 36 pages. DOI: https://doi.org/10.1016/j.neucom.2018.06.056. KDensity: 10.96. Refs: 36.

407. Barreau, Shen. 2025. *Accuracy and Robustness of Weight-Balancing Methods for Training PINNs.* Computer Science > Machine Learning. 39 pages. DOI: https://doi.org/10.48550/arXiv.2501.18582. KDensity: 10.95. Repo. Refs: 60.

408. Zhu, Yin. 2009. *On competitive Lotka-Volterra model in random environments.* Journal of Mathematical Analysis and Applications 357 (1)(2009) 154–170.. 17 pages. DOI: https://doi.org/10.1016/j.jmaa.2009.03.066. KDensity: 10.95. Refs: 59.

409. Brunton, Kutz. 2019. *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control.* Cambridge University Press. 495 pages. DOI: https://doi.org/10.1017/9781108380690. KDensity: 10.9. Repo. Refs: 573.

410. Stein. 1987. *Large Sample Properties of Simulations Using Latin Hypercube Sampling.* Technometrics Volume. 10 pages. DOI: https://doi.org/10.2307/1269769. KDensity: 10.9. Refs: 7.

411. Kirchdoerfer, Ortiz. 2016. *Data-driven computational mechanics.* Computer Methods in Applied Mechanics and Engineering. Volume. 32 pages. DOI: https://doi.org/10.1016/j.cma.2016.02.001. KDensity: 10.88. Refs: 11.

412. Friedrich, Siegert, Peinke, Lück, Siefert, Lindemann, Raethjen, Deuschl, Pfister. 2000. *Extracting model equations from experimental data.* Physics Letters A. Volume 271, Issue. 6

pages. DOI: https://doi.org/10.1016/S0375-9601(00)00334-0. KDensity: 10.84. Refs: 10.

413. Qiao, Özkan, Teich, Hannig. 2020. *The best of both worlds: Combining CUDA graph with an image processing DSL*. 2020 57th ACM/IEEE Design Automation Conference (DAC). 6 pages. DOI: https://doi.org/10.1109/DAC18072.2020.9218531. KDensity: 10.83. Refs: 12.

414. Bettencourt, Johnson, Duvenaud. 2019. *Taylor-Mode Automatic Differentiation for Higher-Order Derivatives in JAX*. Program Transformations @NeurIPS2019 Oral. 14 pages. DOI: NA. KDensity: 10.78. Refs: 7.

415. Srinivasan, NPTEL. 2019. *Application 4 - Solution of PDE/ODE using Neural Networks*. YouTube. 30 pages. URL: https://www.youtube.com/watch?v=LQ33-GeD-4Y. KDensity: 10.77. Refs: 3.

416. Rasmussen, Williams. 2006. *Gaussian Processes for Machine Learning*. The MIT Press. ISBN electronic:9780262256834. 266 pages. DOI: https://doi.org/10.7551/mitpress/3206.001.0001. KDensity: 10.76. Refs: 0.

417. Hopfield, Tank. 1985. *"Neural" computation of decisions in optimization problems*. 13 pages. DOI: http://dx.doi.org/10.1007/BF00339943. KDensity: 10.73. Refs: 31.

418. Karniadakis, Sherwin. 2013. *Spectral/HP Element Methods for Computational Fluid Dynamics*. Oxford University Press, Oxford. 7 pages. DOI: http://dx.doi.org/10.1093/acprof:oso/9780198528692.001.0001. KDensity: 10.72. Refs: 0.

419. McFall, Albert. 2006. *Artificial neural network method for solving boundary value problems with arbitrary irregular boundaries*. Georgia Institute of Technology. 167 pages. DOI: NA. KDensity: 10.64. Refs: 55.

420. Raissi, Karniadakis. 2016. *Deep Multi-fidelity Gaussian Processes*. Computer Science > Machine Learning arXiv:1604.07484. 14 pages. DOI: https://arxiv.org/abs/1604.07484v1. KDensity: 10.64. Refs: 5.

421. Cha, Choi, Büyüköztürk. 2017. *Deep learning-based crack damage detection using convolutional neural networks*. Comput. Aided Civ. Inf. Eng.. 19 pages. DOI: http://dx.doi.org/10.1111/mice.12263. KDensity: 10.52. Refs: 52.

422. Logg, Mardal, Wells. 2012. *Automated solution of differential equations by the finite element method: The FEniCS book*. 722 pages. DOI: https://doi.org/10.1007/978-3-642-23099-8. KDensity: 10.48. Refs: 468.

423. O'Leary. 2022. *Stochastic Physics-Informed Neural Ordinary Differential Equations (SPINODE)*. NA. 100 pages. URL: https://github.com/jtoleary/SPINODE. KDensity: 10.43. Refs: 1.

424. Zingg, Chisholm. 1999. *Runge–Kutta methods for linear ordinary differential equations*. Applied Numerical Mathematics 31 (1999) 227–238. 12 pages. DOI: https://doi.org/10.1016/S0168-9274(98)00129-9. KDensity: 10.42. Refs: 20.

425. Schober, Duvenaud, Hennig. 2014. *Probabilistic ODE Solvers with Runge-Kutta Means*. 18 pages. DOI: https://doi.org/10.48550/arXiv.1406.2582. KDensity: 10.39. Refs: 21.

426. Wu, Zhang. 2017. *Learning physics by data for the motion of a sphere falling in a non-Newtonian fluid*. Communications in Nonlinear Science and Numerical Simulation. Volume 67, February 2019, Pages 577-593. 27 pages. DOI: https://doi.org/10.1016/j.cnsns.2018.05.007. KDensity: 10.38. Refs: 55.

427. Raissi, Perdikaris, Karniadakis. 2021. *Physics informed learning machines*. US Patent. 54 pages. DOI: https://patents.google.com/patent/US10963540B2/en. KDensity: 10.37. Refs: 2.

428. Bec, Khanin. 2007. *Burgers Turbulence*. Physics Reports. Volume 447, Issues 1–2, August 2007, Pages 1-66. 49 pages. DOI: https://doi.org/10.1016/j.physrep.2007.04.002. KDensity: 10.31. Refs: 112.

429. Thuerey, Holl, Mueller, Schnell, Trost, Um. 2021. *Physics-based deep learning*. arXiv preprint arXiv:2109.05237, 2021. 287 pages. DOI: https://doi.org/10.48550/arXiv.2109.05237. KDensity: 10.3. Repo. Refs: 31.

430. Xu, Darve. 2019. *Adversarial Numerical Analysis for Inverse Problems*. 29 pages. DOI: https://doi.org/10.48550/arXiv.1910.06936. KDensity: 10.24. Repo. Refs: 36.

431. Raissi, Perdikaris, Karniadakis. 2018. *Numerical Gaussian processes for time-dependent*

and nonlinear partial differential equations. SIAM Journal on Scientific Computing 40(1), A172–A198 (2018). 51 pages. DOI: https://doi.org/10.1137/17M1120762. KDensity: 10.22. Refs: 37.

432. Gardner. 1988. *The space of interactions in neural network models.* Journal of Physics A: Mathematical and General, Volume 21, Number 1. 10 pages. DOI: http://10.1088/0305-4470/21/1/030. KDensity: 10.2. Refs: 19.

433. Grohs, Hornung, Jentzen, Wurstemberger. 2018. *A proof that artificial neural networks overcome the curse of dimensionality in the numerical approximation of Black-Scholes partial differential equations.* Mem. Amer. Math. Soc.284(2023), no.1410, v+93 pp. 126 pages. DOI: https://arxiv.org/abs/1809.02362v3. KDensity: 10.19. Refs: 103.

434. Raissi, Perdikaris, Karniadakis. 2018. *Physics Informed Neural Networks.* 100 pages. URL: https://maziarraissi.github.io/PINNs/. KDensity: 10.19. Refs: 3.

435. Wang, Wu, Xiao. 2017. *Physics-informed machine learning approach for reconstructing Reynolds stress modeling discrepancies based on DNS data.* Phys. Rev. Fluids. 36 pages. DOI: https://doi.org/10.1103/PhysRevFluids.2.034603. KDensity: 10.16. Refs: 58.

436. Yin, Ban, Rego, Zhang, Cavinato, Humphrey, Karniadakis. 2021. *Simulating progressive intramural damage leading to aortic dissection using an operator-regression neural network.* arXiv:2108.11985 [cs.CE] (25 August 2021).. 47 pages. DOI: https://doi.org/10.48550/arXiv.2108.11985. KDensity: 10.02. Refs: 58.

437. Amsallem, Zahr, Choi, Farhat. 2015. *Design optimization using hyper-reduced-order models.* Struct Multidisc Optim. 22 pages. DOI: https://doi.org/10.1007/s00158-014-1183-y. KDensity: 10.01. Refs: 0.

438. Haenlein, Kaplan. 2019. *A Brief History of Artificial Intelligence: On the Past, Present, and Future of Artificial Intelligence.* California Management Review 61(4):000812561986492. 11 pages. DOI: https://doi.org/10.1177/0008125619864925. KDensity: 10.01. Refs: 28.

439. Gabrielsson, Weiner. 2016. *Pharmacokinetic and pharma-codynamic data analysis: concepts and applications.* (2016) .Lakemedelsakademin i Stockholm AB. 2 pages. DOI: NA.

KDensity: 10. Refs: 0.

440. Caterini, Chang. 2018. *Generic Representation of Neural Networks.* Deep Neural Networks in a Mathematical Framework. Springer Briefs in Computer Science. Springer, Cham.. 91 pages. DOI: https://doi.org/10.1007/978-3-319-75304-1_3. KDensity: 9.97. Refs: 2.

441. Ehrhardt, Gottschalk, Riedlinger. 2025. *Numerical and statistical analysis of NeuralODE with Runge-Kutta time integration.* Machine Learning (cs.LG); Classical Analysis and ODEs (math.CA); Numerical Analysis (math.NA); Probability (math.PR). 29 pages. DOI: https://doi.org/10.48550/arXiv.2503.10729. KDensity: 9.9. Refs: 37.

442. Chen, Fox, Guestrin. 2014. *Stochastic Gradient Hamiltonian Monte Carlo.* ICML 2014 version. 14 pages. DOI: https://arxiv.org/abs/1402.4102v2. KDensity: 9.64. Refs: 22.

443. Agarwal, Dhar. 2014. *Big Data, Data Science, and Analytics: The Opportunity and Challenge for IS Research.* Information Systems Research 25(3):443-448.. 6 pages. DOI: https://doi.org/10.1287/isre.2014.0546. KDensity: 9.5. Refs: 13.

444. Ruder. 2017. *An overview of gradient descent optimization algorithms.* 14 pages. DOI: https://doi.org/10.48550/arXiv.1609.04747. KDensity: 9.21. Repo. Refs: 23.

445. Choi, Boncoraglio, Anderson, Amsallem, Farhat. 2020. *Gradient-based Constrained Optimization Using a Database of Linear Reduced-Order Models.* Journal of Computational Physics. Volume. 31 pages. DOI: https://doi.org/10.1016/j.jcp.2020.109787. KDensity: 8.52. Refs: 0.

446. Kirkpatrick, Gelatt-Jr, Vecchi. 1983. *Optimization by simulated annealing.* Science. 13 May 1983. Vol 220, Issue 4598pp. 671-680. 12 pages. DOI: http://dx.doi.org/10.1126/science.220.4598.671. KDensity: 8.45. Refs: 31.

447. Kutz, Brunton, Brunton, Proctor. 2016. *Dynamic Mode Decomposition: Data-Driven Modeling of Complex Systems.* 241 pages. DOI: NA. KDensity: 8.41. Repo. Refs: 313.

448. Shen, Yang, Zhang. 2019. *Nonlinear Approximation via Compositions.* Neural Networks, Volume 119, November 2019, Pages 74-84. 19 pages. DOI: https://doi.org/10.1016/j.neunet.2019.07.011. KDensity: 7.84. Refs: 52.

449. Graves. 2016. *Adaptive Computation Time for Recurrent Neural Networks.* arxiv [Submitted on 29 Mar 2016 (v1), last revised 21 Feb 2017 (this version, v6)]. 19 pages. DOI: https://arxiv.org/abs/1603.08983v6. KDensity: 7.59. Refs: 36.

450. Ha, Dai, Le. 2017. *Hypernetworks.* arxiv [Submitted on 27 Sep 2016 (v1), last revised 1 Dec 2016 (this version, v4)]. 29 pages. DOI: https://arxiv.org/abs/1609.09106v4. KDensity: 7.27. Refs: 52.

451. Lock, Hassan, Sevilla, Jones. 2023. *Meshing using neural networks for improving the efficiency of computer modelling.* Engineering with Computers. 30 pages. DOI: https://doi.org/10.1007/s00366-023-01812-z. KDensity: 7.18. Refs: 38.

452. E.Weinan, Yu. 2018. *The Deep Ritz method: A deep learning-based numerical algorithm for solving variational problems.* Springer Nature Volume 6, pages 1–12, (2018). 14 pages. DOI: https://doi.org/10.1007/s40304-018-0127-z. KDensity: 7.07. Refs: 12.

453. Owhadi. 2015. *Bayesian Numerical Homogenization.* Multiscale Modeling & Simulation. Vol. 13, Iss. 3 (2015)10.1137/140974596. 17 pages. DOI: https://doi.org/10.1137/140974596. KDensity: 6.35. Refs: 72.

454. Protter, Qiu, Martin. 1998. *Asymptotic error distribution for the Euler scheme with locally Lipschitz coefficients.* Stochastic Processes and their Applications. Volume 130, Issue 4, April 2020, Pages 2296-2311. 16 pages. DOI: https://doi.org/10.1016/j.spa.2019.07.003. KDensity: 6.07. Refs: 28.

455. Kevrekidis, Gear, Hyman, Kevrekidis, Runborg, Theodoropoulos. 2003. *Equation-free, coarse-grained multiscale computation: Enabling microscopic simulators to perform system-level analysis..* Communications in Mathematical Science, 1(4):715–762, 2003.. 74 pages. DOI: http://dx.doi.org/10.4310/CMS.2003.v1.n4.a5. KDensity: 5.84. Refs: 132.

456. Daubechies, DeVore, Foucart, Hanin, Petrova. 2019. *Nonlinear Approximation and (Deep) ReLU Networks.* Constructive Approximation, 55(1), 127-172.. 42 pages. DOI: https://doi.org/10.1007/s00365-021-09548-z. KDensity: 5.6. Refs: 33.

457. Eldan, Shamir. 2016. *The Power of Depth for Feedforward Neural Networks.* 29th Annual

Conference on Learning Theory, PMLR 49:907-940, 2016.. 34 pages. DOI: https://arxiv.org/abs/1512.03965. KDensity: 5.32. Refs: 28.

458. Nguyen, Carilli, Eryilmaz, Singh, Lin, Gimelshein, Desmaison, Yang. 2021. *Accelerating PyTorch with CUDA Graphs*. PyTorch. 100 pages. DOI: NA. KDensity: 5.11. Refs: 0.

459. Liu, Nocedal. 1989. *On the limited memory BFGS method for large scale optimization*. Mathematical Programming. 27 pages. DOI: https://doi.org/10.1007/BF01589116. KDensity: 5.04. Refs: 36.

460. Lu, Mao, Dong. 2017. *Comment on "An Efficient and Stable Hydrodynamic Model With Novel Source Term Discretization Schemes for Overland Flow and Flood Simulations' ' by Xilin Xia et al.*. Water Resources Research. 7 pages. DOI: https://doi.org/10.1002/2017WR021563. KDensity: 4.15. Refs: 7.

461. Andersen, Dahl, Vandenberghe. 2013. *CVXOPT: Convex Optimization*. Astrophysics Source Code Library, record ascl:2008.017. 100 pages. URL: https://github.com/cvxopt/cvxopt. KDensity: 0.12. Refs: 1.

462. Sabne. 2020. *XLA : Compiling Machine Learning for Peak Performance*. Google Research. 100 pages. DOI: NA. KDensity: 0.07. Refs: 0.

2. Supporting

463. Mallat. 2016. *Understanding deep convolutional networks*. Adaptive data analysis: theory and applications' compiled and edited by Norden E. Huang, Ingrid Daubechies and Thomas Y. Hou. 16 pages. DOI: https://doi.org/10.1098/rsta.2015.0203. KDensity: 8.88. Refs: 32.

464. LeCun, Touresky, Hinton, Sejnowski. 1988. *A theoretical framework for back-propagation*. In Proceedings of the 1988 connectionist models summer school, volume 1, pages 21–28. CMU,Pittsburgh, Pa: Morgan Kaufmann, 1988.. 9 pages. DOI: NA. KDensity: 7.66. Refs: 13.

465. Shi, Dao, Tsymbalov, Shapeev, Li, Suresh. 2020. *Metallization of diamond*. 6 pages. DOI:

https://doi.org/10.1073/pnas.2013565117. KDensity: 7.5. Refs: 58.

466. Sutton, Barto. 2018. *Reinforcement Learning: An Introduction, second edition.* NA. 548 pages. DOI: ISBN: 9780262039246. KDensity: 7.01. Refs: 782.

467. Mhaskar, Poggio. 2016. *Deep vs. shallow networks: An approximation theory perspective.* Analysis and Applications. Vol. 14, No. 06, pp. 829-848 (2016). 16 pages. DOI: https://doi.org/10.1142/S0219530516400042. KDensity: 7. Refs: 27.

468. Kingma, Ba. 2014. *Adam: A Method for Stochastic Optimization.* NA. 15 pages. DOI: https://doi.org/10.48550/arXiv.1412.6980. KDensity: 6.53. Refs: 23.

469. Rajan. 2005. *Materials informatics.* Material Today. Volume 8, Issue 10, October 2005, Pages 38-45. 8 pages. DOI: https://doi.org/10.1016/S1369-7021(05)71123-8. KDensity: 6.37. Refs: 58.

470. Yarotsky. 2017. *Error bounds for approximations with deep ReLU networks.* Neural Networks. Volume 94, October 2017, Pages 103-114. 31 pages. DOI: https://doi.org/10.1016/j.neunet.2017.07.002. KDensity: 6.32. Refs: 28.

471. Griewank. 2012. *Who Invented the Reverse Mode of Differentiation?.* 12 pages. DOI: https://api.semanticscholar.org/CorpusID:15568746. KDensity: 6.25. Refs: 13.

472. Khoury, Ioannidis. 2014. *Medicine. Big data meets public health.* Science, 346(6213):1054–1055, 2014.. 4 pages. DOI: https://doi.org/10.1126%2Fscience.aaa2709. KDensity: 5.75. Refs: 15.

473. Draper, Smith. 2014. *Applied regression analysis.* John Wiley & Sons, 2014. 738 pages. DOI: ISBN: 978-0-471-17082-2. KDensity: 5.17. Refs: 342.

474. Hochreiter, Schmidhuber. 1997. *Long Short-Term Memory.* Neural Computation (1997) 9 (8): 1735–1780.. 32 pages. DOI: https://doi.org/10.1162/neco.1997.9.8.1735. KDensity: 5.09. Refs: 41.

475. Stuart. 2010. *Inverse problems: A Bayesian perspective.* Published online by Cambridge University Press: 10 May 2010. 110 pages. DOI: https://doi.org/10.1017/S0962492910000061. KDensity: 4.89. Refs: 230.

476. Dormand, Prince. 1980. *A family of embedded Runge-Kutta formulae.* Journal of Computational and Applied Mathematics. Volume 6, Issue 1, March 1980, Pages 19-26. 8 pages. DOI: https://doi.org/10.1016/0771-050X(80)90013-3. KDensity: 4.88. Refs: 17.

477. Zhou. 2021. *Machine Learning.* Springer Nature Link. 460 pages. DOI: https://doi.org/10.1007/978-981-15-1967-3. KDensity: 4.88. Refs: 0.

478. Chartrand. 2011. *Numerical Differentiation of Noisy, Nonsmooth Data.* ISRN Applied Mathematics. 11 pages. DOI: https://doi.org/10.5402/2011/164564. KDensity: 4.73. Refs: 17.

479. Burgers. 1948. *A Mathematical Model Illustrating the Theory of Turbulence.* Advances in Applied Mechanics. Volume. 29 pages. DOI: https://doi.org/10.1016/S0065-2156(08)70100-5. KDensity: 4.65. Refs: 0.

480. Siegert, Friedrich, b. 1998. *Analysis of data sets of stochastic systems.* Physics Letters A. Volume 243, Issues 5–6, 6 July 1998, Pages 275-280. 7 pages. DOI: https://doi.org/10.1016/S0375-9601(98)00283-7. KDensity: 4.58. Refs: 12.

481. Marx. 2013. *The big challenges of big data.* Nature, 498(7453):255–260, 2013.. 5 pages. DOI: https://doi.org/10.1038/498255a. KDensity: 4.4. Refs: 3.

482. Owhadi, Scovel, Sullivan. 2015. *Brittleness of Bayesian inference under finite information in a continuous world.* Electron. J. Statist. 9 (1) 1 -. 79 pages. DOI: https://doi.org/10.1214/15-EJS989. KDensity: 4.37. Refs: 108.

483. Jin. 2021. *Big-Data-Driven Multi-Scale Experimental Study of Nanostructured Block Copolymer's Dynamic Toughness.* 24 pages. DOI: NA. KDensity: 4.13. Refs: 0.

484. Bottou, Bousquet. 2008. *The Tradeoffs of Large Scale Learning.* Advances in Neural Information Processing Systems} Volume 40. 17 pages. DOI: NA. KDensity: 4.12. Refs: 30.

485. Niyogi, Girosi. 1999. *Generalization bounds for function approximation from scattered noisy data.* Advances in Computational Mathematics. 30 pages. DOI: https://doi.org/10.1023/A:1018966213079. KDensity: 4.07. Refs: 46.

486. Manohar, Brunton, Kutz, Brunton. 2017. *Code supplement to "Data-driven sparse sensor*

placement. K. Manohar, B. W. Brunton, J. N. Kutz, and S. L. Brunton, “Code supplement to”Datadriven sparse sensor placement”.” January 2017. 1 pages. URL: https://github.com/kmanohar/SSPOR_pub. KDensity: 4. Refs: 1.

487. Bodaghi, Wang, Xue, Zheng. 2023. *Effects of antagonistic muscle actuation on the bilaminar structure of ray-finned fish in propulsion*. Journal of Fluid Mechanics. 22 pages. DOI: https://doi.org/10.1017/jfm.2023.839. KDensity: 3.96. Refs: 46.

488. Hinton, Sejnowski. 1986. *Learning and relearning in Boltzmann machines*. Parallel Distributed Processing: Explorations in the Microstructure of Cognition. Volume 1: Foundations, MIT Press, Cambridge, MA. pp 282-317. 37 pages. DOI: NA. KDensity: 3.59. Refs: 25.

489. Koza, III, Stiffelman. 1999. *Genetic Programming as a Darwinian Invention Machine*. Part of the book series: Lecture Notes in Computer Science ((LNCS,volume 1598)). 18 pages. DOI: https://doi.org/10.1007/3-540-48885-5_8. KDensity: 3.55. Refs: 33.

490. Neal. 2011. *MCMC using Hamiltonian dynamics*. NA. 51 pages. DOI: https://doi.org/10.48550/arXiv.1206.1901. KDensity: 3.14. Refs: 48.

491. Griffiths, Higham. 2010. *Numerical methods for ordinary differential equations: initial value problems*. 274 pages. DOI: http://dx.doi.org/10.1007/978-0-85729-148-6. KDensity: 3.03. Refs: 70.

492. Archibald, Fraser, Grattan-Guinness. 2005. *The history of differential equations, 1670–1950*. 66 pages. DOI: https://doi.org/10.14760/OWR-2004-51. KDensity: 2.98. Refs: 159.

493. Calvo, Montijano, Randez. 1990. *A fifth-order interpolant for the Dormand and Prince Runge-Kutta method*. Journal of Computational and Applied Mathematics. Volume 29, Issue. 10 pages. DOI: https://doi.org/10.1016/0377-0427(90)90198-9. KDensity: 2.8. Refs: 11.

494. Dagan, Daskalakis, Dikkala, Kandiros. 2020. *Learning Ising models from one or multiple samples*. 64 pages. DOI: https://doi.org/10.48550/arXiv.2004.09370. KDensity: 2.56. Refs: 67.

495. Butcher. 1987. *The numerical analysis of ordinary differential equations: Runge-Kutta and general linear methods.* 484 pages. DOI: ISBN: 978-0-471-91046-6. KDensity: 2.5. Repo. Refs: 136.

496. DeVore, Ron. 2010. *Approximation using scattered shifts of a multivariate function.* Transactions of the American Mathematical Society. Vol. 362, No. 12 (DECEMBER 2010), pp. 6205-6229 (25 pages). 25 pages. DOI: https://arxiv.org/abs/0802.2517v1. KDensity: 2.48. Refs: 37.

497. Iserles. 2008. *A first course in the numerical analysis of differential equations.* 481 pages. DOI: https://doi.org/10.1017/CBO9780511995569. KDensity: 2.42. Repo. Refs: 6.

498. Hinton, Srivastava, Swersky. 2012. *Neural Networks for Machine Learning. Lecture 6a. Overview of mini-batch gradient descent.* Open Journal of Applied Sciences, Vol.14 No.6, June. 31 pages. DOI: NA. KDensity: 2.32. Refs: 0.

499. Pinkus. 1999. *Approximation theory of the MLP model in neural networks.* 30 pages. DOI: https://doi.org/10.1017/S0962492900002919. KDensity: 2.17. Refs: 7.

500. Mohri, Rostamizadeh, Talwalkar. 2018. *Foundations of Machine Learning, second edition.* The MIT Press. 496 pages. DOI: ISBN: 9780262039406. KDensity: 2.16. Refs: 0.

501. Hall. 2005. *Generalized Method of Moments.* In book A Companion to Theoretical Econometrics. 16 pages. DOI: https://doi.org/10.1002/9780470996249.ch12. KDensity: 2.13. Refs: 15.

502. Carpenter, Hoffman, Brubaker, Lee, Li, Betancourt. 2015. *The Stan Math Library: Reverse-Mode Automatic Differentiation in C++.* arxiv [Submitted on 23 Sep 2015]. 96 pages. DOI: https://arxiv.org/abs/1509.07164v1. KDensity: 2.07. Refs: 33.

503. Mhaskar, Micchelli. 1992. *Approximation by superposition of sigmoidal and radial basis functions.* Advances in Applied Mathematics. Volume 13, Issue 3, September 1992, Pages 350-373. 24 pages. DOI: https://doi.org/10.1016/0196-8858(92)90016-P. KDensity: 2.04. Refs: 25.

504. Yadan. 2019. *Hydra - a framework for elegantly configuring complex applications.* GitHub.

1 pages. URL: https://github.com/facebookresearch/hydra. KDensity: 2. Refs: 0.

505. Plaut, Nowlan, Hinton. 1986. *Experiments on Learning by Back Propagation.* 45 pages. DOI: NA. KDensity: 1.82. Refs: 11.

506. Garey, Johnson. 1979. *Computers and Intractability: A Guide to the Theory of NP-Completeness.* Journal of Symbolic Logic 48 (2):498-500 (1983). 175 pages. DOI: NA. KDensity: 1.69. Refs: 731.

507. Betancourt. 2017. *A Conceptual Introduction to Hamiltonian Monte Carlo.* NA. 60 pages. DOI: https://arxiv.org/abs/1701.02434. KDensity: 1.65. Refs: 32.

508. Rumelhart, Hinton, Williams. 1986. *Learning internal representations by error propagation.* 45 pages. DOI: https://doi.org/10.1016/B978-1-4832-1446-7.50035-2. KDensity: 1.35. Refs: 0.

509. Neal. 2012. *Bayesian Learning for Neural Networks.* Springer New York, NY. 195 pages. DOI: https://doi.org/10.1007/978-1-4612-0745-0. KDensity: 1.15. Refs: 70.

510. Driscoll, Hale, Trefethen. 2014. *Chebfun Guide.* 212 pages. DOI: NA. KDensity: 1.11. Repo. Refs: 1.

511. Whitham. 2011. *Linear and Nonlinear Waves.* Wiley. Applied Mathematics in Science. 660 pages. DOI: ISBN: 978-0-471-35942-5. KDensity: 1.1. Refs: 0.

512. Chandrasekhar. 1943. *Stochastic problems in Physics and Astronomy.* Reviews of Modern Physics. 89 pages. DOI: https://doi.org/10.1103/REVMODPHYS.15.1. KDensity: 1.01. Refs: 73.

513. Golub, Loan. 2012. *Matrix Computations.* 780 pages. DOI: NA. KDensity: 0.69. Refs: 777.

514. Harry. 1915. *Some Recent Researches on the Motion of Fluids.* Monthly Weather Review, vol. 43, issue 4, p. 163. 8 pages. DOI: https://doi.org/10.1175/1520-0493(1915)43%3C163:SRROTM%3E2.0.CO;2. KDensity: 0.63. Refs: 65.

515. Pontryagin. 1962. *Mathematical Theory of Optimal Processes.* Routledge. 385 pages. DOI: https://doi.org/10.1201/9780203749319. KDensity: 0.44. Refs: 40.

516. Sakurai. 1995. *Modern quantum mechanics, revised edition.* Sakurai, J. J. and Commins, E. D. Modern quantum mechanics, revised edition. AAPT, 1995.. 635 pages. DOI: https://doi.org/10.1119/1.17781. KDensity: 0.34. Refs: 0.

517. Daubechies. 1992. *Ten Lectures on Wavelets.* CBMS-NSF Regional Conference Series in Applied Mathematics. 344 pages. DOI: https://doi.org/10.1137/1.9781611970104. KDensity: 0.27. Refs: 11.

518. Seefeldt, Sondak, Hensinger, Phipps, Foucar, P., C., N., M., D., Sibusiso, M., M., J., J., G., T., Sean, Paul, M., E., Sidafa. 2017. *Drekar v.2.0.* Sandia National Laboratories (SNL-NM), Albuquerque, NM (United States). 100 pages. DOI: https://doi.org/10.11578/dc.20220414.50. KDensity: 0.21. Repo. Refs: 0.

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: 462 citations
- Supporting folder: 56 citations
- Unreferenced folder: 0 citations
- Scientific Machine Learning (Core): 462 citations
- Supporting Papers: 56 citations
- No Rated Papers: 0 citations