

Projects 2023

Approximation theorems with neural networks

- Breaking the Curse of Dimensionality with Convex Neural Networks, by Francis Bach. The Journal of Machine Learning Research 18 (2017), no. 1, 629- 681. <https://arxiv.org/pdf/1412.8690.pdf>
- A Functional Perspective on Learning Symmetric Functions with Neural Networks, Aaron Zweig, Joan Bruna. <https://arxiv.org/pdf/2008.06952.pdf>
- Lower bounds for artificial neural network approximations: A proof that shallow neural networks fail to overcome the curse of dimensionality, by Philipp Grohs, Shokhrukh Ibragimov, Arnulf Jentzen, Sarah Koppensteiner. <https://arxiv.org/pdf/2103.04488.pdf>
- Deep Neural Network Approximation Theory. Elbrächter, Dennis; Perekrestenko, Dmytro ; Grohs, Philipp; Bölskei, Helmut. In: IEEE TRANSACTIONS ON INFORMATION THEORY, Vol. 67, No. 5, 9363169, 05.2021, p. 2581-2623. <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=9363169>
- The Power of Depth for Feedforward Neural Networks, by Ronen Eldan, Ohad Shamir. <https://arxiv.org/pdf/1512.03965.pdf>
- Deep neural network approximation theory for high-dimensional functions, Pierfrancesco Beneventano, Patrick Cheridito, Robin Graeber, Arnulf Jentzen, and Benno Kuckuckhtps. <https://arxiv.org/pdf/2112.14523.pdf>
-
-

Barron spaces

- The Barron Space and the Flow-induced Function Spaces for Neural Network Models, by Weinan E, Chao Ma, Lei Wu, <https://arxiv.org/abs/1906.08039>
- Barron Spaces and the Compositional Function Spaces for Neural Network Models, by Weinan E, Chao Ma, Lei Wu, <https://arxiv.org/pdf/1906.08039.pdf>
-

Geometric deep learning, including graph learning

- Geometric Deep Learning: Grids, Groups, Graphs, Geodesics, and Gauges, Michael M. Bronstein, Joan Bruna, Taco Cohen, Petar Veličković, <https://arxiv.org/abs/2104.13478>
- Geometric deep learning: going beyond Euclidean data by Michael M Bronstein, Joan Bruna, Yann LeCun, Arthur Szlam, and Pierre Vandergheynst, IEEE Signal Processing Magazine, 34(4):18–42, 2017
- Generalizing convolutional neural networks for equivariance to lie groups on arbitrary continuous data, by M Finzi, S Stanton, P Izmailov, <http://proceedings.mlr.press/v119/finzi20a/finzi20a.pdf>
- A theoretical and computational framework for isometry invariant recognition of point cloud data, by Facundo Mémoli and Guillermo Sapiro. Foundations of Computational Mathematics, 5(3):313–347, 2005. <https://link.springer.com/content/pdf/10.1007/s10208-004-0145-y.pdf>
- Graph Learning: A Survey, Feng Xia, Ke Sun, Shuo Yu, Abdul Aziz, Liangtian Wan, Shirui Pan, Huan Liu, <https://arxiv.org/pdf/2105.00696.pdf>
-

Graph neural networks

- Graph Neural Networks: A Review of Methods and Applications, by Jie Zhou, Ganqu Cui, Shengding Hu, Zhengyan Zhang, Cheng Yang, Zhiyuan Liu, Lifeng Wang, Changcheng Li, Maosong Sun, <https://arxiv.org/ftp/arxiv/papers/1812/1812.08434.pdf>
- Computing Graph Neural Networks: A Survey from Algorithms to Accelerators, Abadal et al. <https://dl.acm.org/doi/fullHtml/10.1145/3477141>
- The Graph Neural Network Model. Franco Scarselli, Marco Gori, Ah Chung Tsoi, Markus Hagenbuchner, and G. Monfardini. 2009.. IEEE Trans. Neural Netw. 20, 1 (2009), 61–80.
- Computational capabilities of graph neural networks. Franco Scarselli, Marco Gori, Ah Chung Tsoi, Markus Hagenbuchner, and Gabriele Monfardini. 2009.. IEEE Trans. Neural Netw. 20, 1 (2009), 81–102.
- On Graph Neural Networks versus Graph-Augmented MLPs, by Lei Chen, Zhengdao Chen, Joan Bruna. <https://arxiv.org/pdf/2010.15116.pdf>

Deep Belief Networks

- Restricted Boltzmann Machine and Deep Belief Network: Tutorial and Survey, by Benjamin Ghogho, Ali Ghodsi, Fakhri Karray, Mark Crowley. <https://arxiv.org/pdf/2107.12521.pdf>

Generative adversarial networks.

Manifold learning (see link <http://bactra.org/notebooks/manifold-learning.html>)

- Belkin, M. and Niyogi, P. Laplacian eigenmaps for dimensionality reduction and data representation. Neural Computation, 15(6):1373–1396, 2003
- Coifman, R. R. and Lafon, S. Diffusion maps. Applied and Computational Harmonic Analysis, 21(1):5–30, 2006
- Testing the Manifold Hypothesis, Charles Fefferman, Sanjoy Mitter, Hariharan Narayanan. https://www.mit.edu/~mitter/publications/121_Testing_Manifold.pdf
- Lawrence K. Saul and Sam T. Roweis, "Think Globally, Fit Locally: Supervised Learning of Low Dimensional Manifolds", Journal of Machine Learning Research 4 (2003): 119—155. <https://www.jmlr.org/papers/volume4/saul03a/saul03a.pdf>
- Evarist Giné and Vladimir Koltchinskii, "Empirical graph Laplacian approximation of Laplace--Beltrami operators: Large sample results", in High Dimensional Probability : Proceedings of the Fourth International Conference (Giné Koltchinskii, Li and Zinn, eds.), <https://arxiv.org/pdf/math/0612777.pdf>
- Sayan Mukherjee, Qiang Wu, Ding-Xuan Zhou, "Learning gradients on manifolds", Bernoulli 16 (2010): 181--207, <https://arxiv.org/pdf/1002.4283.pdf>

Intrinsic dimension

Sketching

- *Sketching Datasets for Large-Scale Learning (long version)*, by Rémi Gribonval, Antoine Chatalic, Nicolas Keriven, Vincent Schellekens, Laurent Jacques, Philip Schniter, <https://arxiv.org/abs/2008.01839>

- Statistical properties of sketching algorithms, by Daniel Ahfock, William J. Astle, Sylvia Richardson. <https://arxiv.org/abs/1706.03665>
- A Statistical Perspective on Randomized Sketching for Ordinary Least-Squares, by Raskutti, G., & Mahoney, M. W. <https://jmlr.csail.mit.edu/papers/volume17/15-440/15-440.pdf>
- Asymptotics for sketching in least squares regression, by Dobriban, Edgar, and Sifan Liu. <https://arxiv.org/abs/1810.06089>
-

Wasserstein gradient flows

- Entropic Wasserstein Gradient Flows, by Gabriel Peyré, <https://arxiv.org/abs/1502.06216>
- On Sparsity in Overparametrised Shallow ReLU Networks, Jaume de Dios, Joan Bruna, <https://arxiv.org/pdf/2006.10225.pdf>
- Computational optimal transport: With applications to data science, by G Peyré, M Cuturi - Foundations and Trends in Machine Learning, 2019
- On Sparsity in Overparametrised Shallow ReLU Networks, by Jaume de Dios and Joan Bruna. <https://arxiv.org/pdf/2006.10225.pdf>
-

Reinforcement learning

- Reinforcement Learning: An Introduction, by Richard S. Sutton and Andrew G. Barto, Second Edition. MIT Press, Cambridge, MA, 2018, <http://www.incompleteideas.net/book/the-book-2nd.html>
-

Deep learning and inverse problems (including imaging)

- Deep Learning Techniques for Inverse Problems in Imaging, Gregory Ongie, Ajil Jalal, Christopher A. Metzler, Richard G. Baraniuk, Alexandros G. Dimakis, Rebecca Willett, <https://arxiv.org/pdf/2005.06001.pdf>
- Algorithm unrolling: Interpretable, efficient deep learning for signal and image processing. By Monga, V., Li, Y., and Eldar, Y. C. (2021) IEEE Signal Processing Magazine, 38(2):18–44.
- Image reconstruction: From sparsity to data-adaptive methods and machine learning. Proceedings of the IEEE, 108(1):86–109 (2019), by Ravishankar, S., Ye, J. C., and Fessler, J. A.
- NETT: solving inverse problems with deep neural networks, by Housen Li, Johannes Schwab, Stephan Antholzer and Markus Haltmeier, <https://iopscience.iop.org/article/10.1088/1361-6420/ab6d57>
- Compressed Sensing using Generative Models, Ashish Bora, Ajil Jalal, Eric Price, Alexandros G. Dimakis. <https://arxiv.org/pdf/1703.03208.pdf>
- The troublesome kernel -- On hallucinations, no free lunches and the accuracy-stability trade-off in inverse problems, Nina M. Gottschling, Vegard Antun, Anders C. Hansen, Ben Adcock. <https://arxiv.org/pdf/2001.01258.pdf>
- On instabilities of deep learning in image reconstruction and the potential costs of AI. By Antun, V., Renna, F., Poon, C., Adcock, B., and Hansen, A. C. (2020). Proceedings of the National Academy of Sciences, 117(48):30088–30095.
- Solving ill-posed inverse problems using iterative deep neural networks, by Adler, J. and Oktem, O. (2017). Inverse Problems, 33(12):124007.
- Learned primal-dual reconstruction, by Adler, J. and Oktem, IEEE Transactions on Medical Imaging, 37 (2018), pp. 1322–1332
- Solving inverse problems using data-driven models. Arridge, S., Maass, P., Oktem, O., and Schoenlieb, C.-B. (2019). Acta Numerica, 28:1–174.

- Deep learning architectures for nonlinear operator functions and nonlinear inverse problems, by Maarten V. de Hoop, Matti Lassas, Christopher A. Wong. <https://arxiv.org/pdf/1912.11090.pdf>

Implicit bias of gradient descent

- The implicit bias of gradient descent on separable data., by Daniel Soudry, Elad Hoffer, Mor Shpigel Nacson, Suriya Gunasekar, and Nathan Srebro. The Journal of Machine Learning Research, 19(1):2822–2878, 2018. <https://www.jmlr.org/papers/volume19/18-188/18-188.pdf>
- In Search of the Real Inductive Bias: On the Role of Implicit Regularization in Deep Learning, by Behnam Neyshabur, Ryota Tomioka, Nathan Srebro, <https://arxiv.org/pdf/1412.6614.pdf>
- The implicit bias of gradient descent on nonseparable data, by Ziwei Ji and Matus Telgarsky. <http://proceedings.mlr.press/v99/ji19a/ji19a.pdf>.
- On the Optimization of Deep Networks: Implicit Acceleration by Overparameterization, by Sanjeev Arora, Nadav Cohen, Elad Hazan. <https://arxiv.org/pdf/1802.06509.pdf>
- Gradient Descent Converges to Minimizers, by Jason D. Lee, Max Simchowitz, Michael I. Jordan, Benjamin Recht. <https://arxiv.org/pdf/1602.04915.pdf>.
- Implicit Bias of Gradient Descent for Wide Two-layer Neural Networks Trained with the Logistic Loss, by Lenaic Chizat, Francis Bach. <https://core.ac.uk/reader/287425490>
-

Neural networks and ODE/PDE

- Neural ordinary differential equations, Ricky TQ Chen, Yulia Rubanova, Jesse Bettencourt, and David Duvenaud, <https://arxiv.org/pdf/1806.07366.pdf>
- Dissecting neural odes, by S Massaroli, M Poli, J Park, <https://proceedings.neurips.cc/paper/2020/file/293835c2cc75b585649498ee74b395f5-Paper.pdf>
- Deep neural networks motivated by partial differential equations, by L Ruthotto, E Haber - Journal of Mathematical Imaging and Vision, 2020, <https://link.springer.com/article/10.1007/s10851-019-00903-1>
-