

- Q. Nguyen. On connected sublevel sets in deep learning. In K. Chaudhuri and R. Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 4790–4799. PMLR, 09–15 Jun 2019. URL <https://proceedings.mlr.press/v97/nguyen19a.html>.
- X. Ni, Z. Yan, T. Wu, J. Fan, and C. Chen. A region-of-interest-reweight 3D convolutional neural network for the analytics of brain information processing. In A. F. Frangi, J. A. Schnabel, C. Davatzikos, C. Alberola-López, and G. Fichtinger, editors, *Medical Image Computing and Computer Assisted Intervention – MICCAI 2018*, pages 302–310, Cham, 2018. Springer International Publishing. ISBN 978-3-030-00931-1.
- N. I. of Standards and Technology. NIST TrojAI Competition Dataset. <https://pages.nist.gov/trojai/docs/index.html#round-1>.
- C. Olah, A. Mordvintsev, and L. Schubert. Feature visualization. *Distill*, 2017. doi: 10.23915/distill.00007. <https://distill.pub/2017/feature-visualization>.
- C. Olah, A. Satyanarayan, I. Johnson, S. Carter, L. Schubert, K. Ye, and A. Mordvintsev. The building blocks of interpretability. *Distill*, 2018. doi: 10.23915/distill.00010. <https://distill.pub/2018/building-blocks>.
- M. Papillon, S. Sanborn, M. Hajij, and N. Miolane. Architectures of topological deep learning: A survey on topological neural networks, 2023. URL <https://arxiv.org/abs/2304.10031>.
- G. Petri and A. Leitão. On the topological expressive power of neural networks. In *TDA & Beyond*, 2020. URL <https://openreview.net/forum?id=I44kJPuvqPD>.
- L. Prechelt. *Early Stopping - But When?*, pages 55–69. Springer Berlin Heidelberg, Berlin, Heidelberg, 1998. ISBN 978-3-540-49430-0. doi: 10.1007/3-540-49430-8\_3. URL [https://doi.org/10.1007/3-540-49430-8\\_3](https://doi.org/10.1007/3-540-49430-8_3).
- S. J. D. Prince. *Understanding Deep Learning*. MIT Press, 2023. URL <http://udlbook.com>.
- E. Purvine, D. Brown, B. Jefferson, C. Joslyn, B. Praggastis, A. Rathore, M. Shapiro, B. Wang, and Y. Zhou. Experimental observations of the topology of convolutional neural network activations. In *Proceedings of the Thirty-Seventh AAAI Conference on Artificial Intelligence and Thirty-Fifth Conference on Innovative Applications of Artificial Intelligence and Thirteenth Symposium on Educational Advances in Artificial Intelligence, AAAI’23/IAAI’23/EAAI’23*. AAAI Press, 2023. ISBN 978-1-57735-880-0. doi: 10.1609/aaai.v37i8.26134. URL <https://doi.org/10.1609/aaai.v37i8.26134>.
- A. Radford, L. Metz, and S. Chintala. Unsupervised representation learning with deep convolutional generative adversarial networks. In Y. Bengio and Y. LeCun, editors, *4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings*, 2016. URL <http://arxiv.org/abs/1511.06434>.

- K. N. Ramamurthy, K. Varshney, and K. Mody. Topological data analysis of decision boundaries with application to model selection. In K. Chaudhuri and R. Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 5351–5360. PMLR, 09–15 Jun 2019. URL <https://proceedings.mlr.press/v97/ramamurthy19a.html>.
- A. Rathore, N. Chalapathi, S. Palande, and B. Wang. TopoAct: Visually exploring the shape of activations in deep learning. *Computer Graphics Forum*, 40(1):382–397, 2021. doi: <https://doi.org/10.1111/cgf.14195>. URL <https://onlinelibrary.wiley.com/doi/abs/10.1111/cgf.14195>.
- A. Rathore, Y. Zhou, V. Srikumar, and B. Wang. TopoBERT: Exploring the topology of fine-tuned word representations. *Information Visualization*, 22(3):186–208, 2023. doi: [10.1177/14738716231168671](https://doi.org/10.1177/14738716231168671). URL <https://doi.org/10.1177/14738716231168671>.
- G. Reeb. Sur les points singuliers d’une forme de Pfaff complètement intégrable ou d’une fonction numérique [On the singular points of a completely integrable Pfaff form or of a numerical function]. *Comptes Rendus Acad. Sciences Paris*, 222:847–849, 1946.
- M. W. Reimann, M. Nolte, M. Scolamiero, K. Turner, R. Perin, G. Chindemi, P. Dłotko, R. Levi, K. Hess, and H. Markram. Cliques of neurons bound into cavities provide a missing link between structure and function. *Frontiers in Computational Neuroscience*, 11, 2017. ISSN 1662-5188. doi: [10.3389/fncom.2017.00048](https://doi.org/10.3389/fncom.2017.00048). URL <https://www.frontiersin.org/articles/10.3389/fncom.2017.00048>.
- B. Rieck. On the expressivity of persistent homology in graph learning, 2023. URL <https://arxiv.org/abs/2302.09826>.
- B. Rieck, M. Togninalli, C. Bock, M. Moor, M. Horn, T. Gumbsch, and K. Borgwardt. Neural persistence: A complexity measure for deep neural networks using algebraic topology. In *International Conference on Learning Representations*, 2019. URL <https://openreview.net/forum?id=ByxkijC5FQ>.
- M. S. M. Sajjadi, O. Bachem, M. Lucic, O. Bousquet, and S. Gelly. Assessing generative models via precision and recall. In S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 31. Curran Associates, Inc., 2018. URL [https://proceedings.neurips.cc/paper\\_files/paper/2018/file/f7696a9b362ac5a51c3dc8f098b73923-Paper.pdf](https://proceedings.neurips.cc/paper_files/paper/2018/file/f7696a9b362ac5a51c3dc8f098b73923-Paper.pdf).
- B. Schweinhart. Persistent homology and the upper box dimension. *Discrete & Computational Geometry*, 65(2):331–364, Mar 2021. ISSN 1432-0444. doi: [10.1007/s00454-019-00145-3](https://doi.org/10.1007/s00454-019-00145-3). URL <https://doi.org/10.1007/s00454-019-00145-3>.
- B. Settles. Active learning literature survey. Computer Sciences Technical Report 1648, University of Wisconsin–Madison, 2009. URL <http://axon.cs.byu.edu/~martinez/classes/778/Papers/settles.activelearning.pdf>.

- D. R. Sheehy. Linear-size approximations to the Vietoris–Rips filtration. *Discrete & Computational Geometry*, 49(4):778–796, Jun 2013. ISSN 1432-0444. doi: 10.1007/s00454-013-9513-1. URL <https://doi.org/10.1007/s00454-013-9513-1>.
- R. Sibson. SLINK: An optimally efficient algorithm for the single-link cluster method. *The Computer Journal*, 16(1):30–34, 01 1973. ISSN 0010-4620. doi: 10.1093/comjnl/16.1.30. URL <https://doi.org/10.1093/comjnl/16.1.30>.
- U. Simsekli, O. Sener, G. Deligiannidis, and M. A. Erdogdu. Hausdorff dimension, heavy tails, and generalization in neural networks. In H. Larochelle, M. Ranzato, R. Hadsell, M. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 5138–5151. Curran Associates, Inc., 2020. URL [https://proceedings.neurips.cc/paper\\_files/paper/2020/file/37693cfc748049e45d87b8c7d8b9aacd-Paper.pdf](https://proceedings.neurips.cc/paper_files/paper/2020/file/37693cfc748049e45d87b8c7d8b9aacd-Paper.pdf).
- G. Singh, F. Memoli, and G. Carlsson. Topological Methods for the Analysis of High Dimensional Data Sets and 3D Object Recognition. In M. Botsch, R. Pajarola, B. Chen, and M. Zwicker, editors, *Eurographics Symposium on Point-Based Graphics*. The Eurographics Association, 2007. ISBN 978-3-905673-51-7. doi: 10.2312/SPBG/SPBG07/091-100.
- Y. Skaf and R. Laubenbacher. Topological data analysis in biomedicine: A review. *Journal of Biomedical Informatics*, 130:104082, 2022. ISSN 1532-0464. doi: <https://doi.org/10.1016/j.jbi.2022.104082>. URL <https://www.sciencedirect.com/science/article/pii/S1532046422000983>.
- C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich. Going deeper with convolutions. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1–9, Los Alamitos, CA, USA, Jun 2015. IEEE Computer Society. doi: 10.1109/CVPR.2015.7298594. URL <https://doi.ieeecomputersociety.org/10.1109/CVPR.2015.7298594>.
- R. E. Tarjan. Efficiency of a good but not linear set union algorithm. *J. ACM*, 22(2): 215–225, apr 1975. ISSN 0004-5411. doi: 10.1145/321879.321884. URL <https://doi.org/10.1145/321879.321884>.
- The GUDHI Project. *GUDHI User and Reference Manual*. GUDHI Editorial Board, 2015. URL <http://gudhi.gforge.inria.fr/doc/latest/>.
- I. Tolstikhin, O. Bousquet, S. Gelly, and B. Schoelkopf. Wasserstein auto-encoders. In *International Conference on Learning Representations*, 2018. URL <https://openreview.net/forum?id=HkL7n1-0b>.
- H. J. van Veen, N. Saul, D. Eargle, and S. W. Mangham. Kepler Mapper: A flexible Python implementation of the Mapper algorithm. *Journal of Open Source Software*, 4(42):1315, 2019. doi: 10.21105/joss.01315. URL <https://doi.org/10.21105/joss.01315>.
- J. Von Rohrscheidt and B. Rieck. Topological singularity detection at multiple scales. In *International Conference on Machine Learning, ICML 2023, 23-29 July 2023, Honolulu, Hawaii, USA*, volume 202 of *Proceedings of Machine Learning Research*. PMLR, 2023.