

A Living Review of Machine Learning for Particle Physics

ABSTRACT: Modern machine learning techniques, including deep learning, is rapidly being applied, adapted, and developed for high energy physics. The goal of this document is to provide a nearly comprehensive list of citations for those developing and applying these approaches to experimental, phenomenological, or theoretical analyses. As a living document, it will be updated as often as possible to incorporate the latest developments. A list of proper (unchanging) reviews can be found within. Papers are grouped into a small set of topics to be as useful as possible. Suggestions are most welcome.

The purpose of this note is to collect references for modern machine learning as applied to particle physics. A minimal number of categories is chosen in order to be as useful as possible. Note that papers may be referenced in more than one category. The fact that a paper is listed in this document does not endorse or validate its content - that is for the community (and for peer-review) to decide. Furthermore, the classification here is a best attempt and may have flaws - please let us know if (a) we have missed a paper you think should be included, (b) a paper has been misclassified, or (c) a citation for a paper is not correct or if the journal information is now available. In order to be as useful as possible, this document will continue to evolve so please check back before you write your next paper.

- Reviews.
 - Modern reviews [1–7]
 - Classical papers [8, 9]
- Classification.
 - Parameterized classifiers [10, 11].
 - Representations
 - * Jet images [12–22]
 - * Event images [17, 23–25]
 - * Sequences [23, 26]
 - * Trees [27, 28]
 - * Graphs [29–37]
 - * Sets (point clouds) [38, 39]
 - * Physics-inspired basis [40–44]
 - Targets
 - * W/Z tagging [15, 19, 27, 45, 46]
 - * $H \rightarrow b\bar{b}$ [17, 34, 45, 47, 48]
 - * quarks and gluons [16, 20, 28, 32, 49–51]
 - * top quark tagging [6, 14, 21, 22, 35, 44, 49, 52]
 - * strange jets [53]
 - * b -tagging [26, 54, 55]
 - * BSM particles [34, 37, 47, 56–58]
 - * Particle identification [33, 59–62]

- * Neutrino Detectors [63–69]
 - * Tracking [30, 70–72]
 - * Heavy ions [50, 73]
- Learning strategies
 - * Weak supervision [18, 74–82]
 - * Unsupervised [83–86]
- Fast inference
 - * Software [23, 58, 87–90]
 - * Hardware/firmware [91–93]
- Regression.
 - Pileup [24, 31, 94, 95]
 - Calibration [61, 96–100]
 - Recasting [101, 102]
 - Matrix elements [103]
 - Parameter estimation [104]
- Decorrelation methods [57, 105–117]
- Generative models / density estimation.
 - GANs [118]: [61, 62, 119–149]
 - Autoencoders [134, 150]
 - Physics-inspired [151, 152]
 - Normalizing flows [153]: [154–160]
 - Phase space generation [157–159, 161–163]
 - Gaussian processes [102, 164]
- Anomaly detection [76, 77, 82, 85, 86, 160, 165? –180]
- Simulation-based (‘likelihood-free’) Inference.
 - Overview [181]
 - Parameter estimation [11, 182–188]
 - Unfolding [125, 138, 189–195]

- Domain adaptation [11, 182, 196]
- BSM [176, 179, 184–188]
- Uncertainty Quantification.
 - Interpretability [15, 52, 197]
 - Estimation [19, 198, 199]
 - Mitigation [105, 114, 200]
 - Uncertainty-aware inference [201–204]
- Experimental results. *This section is incomplete as there are many results that directly and indirectly (e.g. via flavor tagging) use modern machine learning techniques. We will try to highlight experimental results that use deep learning in a critical way for the final analysis sensitivity.*
 - Final analysis discriminate for searches [82, 205, 206].

References

- [1] A. J. Larkoski, I. Moult and B. Nachman, *Jet Substructure at the Large Hadron Collider: A Review of Recent Advances in Theory and Machine Learning*, *Phys. Rept.* **841** (2020) 1–63, [1709.04464].
- [2] D. Guest, K. Cranmer and D. Whiteson, *Deep Learning and its Application to LHC Physics*, 1806.11484.
- [3] K. Albertsson et al., *Machine Learning in High Energy Physics Community White Paper*, 1807.02876.
- [4] A. Radovic, M. Williams, D. Rousseau, M. Kagan, D. Bonacorsi, A. Himmel et al., *Machine learning at the energy and intensity frontiers of particle physics*, *Nature* **560** (2018) 41–48.
- [5] G. Carleo, I. Cirac, K. Cranmer, L. Daudet, M. Schuld, N. Tishby et al., *Machine learning and the physical sciences*, *Rev. Mod. Phys.* **91** (2019) 045002, [1903.10563].
- [6] A. Butter et al., *The Machine Learning Landscape of Top Taggers*, *SciPost Phys.* **7** (2019) 014, [1902.09914].
- [7] D. Bourilkov, *Machine and Deep Learning Applications in Particle Physics*, *Int. J. Mod. Phys. A* **34** (2020) 1930019, [1912.08245].
- [8] B. H. Denby, *Neural Networks and Cellular Automata in Experimental High-energy Physics*, *Comput. Phys. Commun.* **49** (1988) 429–448.
- [9] L. Lonnblad, C. Peterson and T. Rognvaldsson, *Finding Gluon Jets With a Neural Trigger*, *Phys. Rev. Lett.* **65** (1990) 1321–1324.
- [10] P. Baldi, K. Cranmer, T. Fausett, P. Sadowski and D. Whiteson, *Parameterized neural networks for high-energy physics*, *Eur. Phys. J.* **C76** (2016) 235, [1601.07913].
- [11] K. Cranmer, J. Pavez and G. Louppe, *Approximating Likelihood Ratios with Calibrated Discriminative Classifiers*, 1506.02169.
- [12] J. Pumplin, *How to tell quark jets from gluon jets*, *Phys. Rev. D* **44** (1991) 2025–2032.
- [13] J. Cogan, M. Kagan, E. Strauss and A. Schwartzman, *Jet-Images: Computer Vision Inspired Techniques for Jet Tagging*, *JHEP* **02** (2015) 118, [1407.5675].
- [14] L. G. Almeida, M. Backović, M. Cliche, S. J. Lee and M. Perelstein, *Playing Tag with ANN: Boosted Top Identification with Pattern Recognition*, *JHEP* **07** (2015) 086, [1501.05968].
- [15] L. de Oliveira, M. Kagan, L. Mackey, B. Nachman and A. Schwartzman, *Jet-images — deep learning edition*, *JHEP* **07** (2016) 069, [1511.05190].

- [16] ATLAS COLLABORATION collaboration, *Quark versus Gluon Jet Tagging Using Jet Images with the ATLAS Detector*, Tech. Rep. ATL-PHYS-PUB-2017-017, CERN, Geneva, Jul, 2017.
- [17] J. Lin, M. Freytsis, I. Moulton and B. Nachman, *Boosting $H \rightarrow b\bar{b}$ with Machine Learning*, *JHEP* **10** (2018) 101, [1807.10768].
- [18] P. T. Komiske, E. M. Metodiev, B. Nachman and M. D. Schwartz, *Learning to classify from impure samples with high-dimensional data*, *Phys. Rev. D* **98** (2018) 011502, [1801.10158].
- [19] J. Barnard, E. N. Dawe, M. J. Dolan and N. Rajcic, *Parton Shower Uncertainties in Jet Substructure Analyses with Deep Neural Networks*, *Phys. Rev.* **D95** (2017) 014018, [1609.00607].
- [20] P. T. Komiske, E. M. Metodiev and M. D. Schwartz, *Deep learning in color: towards automated quark/gluon jet discrimination*, *JHEP* **01** (2017) 110, [1612.01551].
- [21] G. Kasieczka, T. Plehn, M. Russell and T. Schell, *Deep-learning Top Taggers or The End of QCD?*, *JHEP* **05** (2017) 006, [1701.08784].
- [22] S. Macaluso and D. Shih, *Pulling Out All the Tops with Computer Vision and Deep Learning*, *JHEP* **10** (2018) 121, [1803.00107].
- [23] T. Q. Nguyen, D. Weitekamp, D. Anderson, R. Castello, O. Cerri, M. Pierini et al., *Topology classification with deep learning to improve real-time event selection at the LHC*, *Comput. Softw. Big Sci.* **3** (2019) 12, [1807.00083].
- [24] ATLAS COLLABORATION collaboration, *Convolutional Neural Networks with Event Images for Pileup Mitigation with the ATLAS Detector*, Tech. Rep. ATL-PHYS-PUB-2019-028, CERN, Geneva, Jul, 2019.
- [25] M. Andrews, M. Paulini, S. Gleyzer and B. Poczos, *End-to-End Physics Event Classification with the CMS Open Data: Applying Image-based Deep Learning on Detector Data to Directly Classify Collision Events at the LHC*, 1807.11916.
- [26] D. Guest, J. Collado, P. Baldi, S.-C. Hsu, G. Urban and D. Whiteson, *Jet Flavor Classification in High-Energy Physics with Deep Neural Networks*, *Phys. Rev.* **D94** (2016) 112002, [1607.08633].
- [27] G. Louppe, K. Cho, C. Becot and K. Cranmer, *QCD-Aware Recursive Neural Networks for Jet Physics*, 1702.00748.
- [28] T. Cheng, *Recursive Neural Networks in Quark/Gluon Tagging*, 1711.02633.
- [29] I. Henrion, K. Cranmer, J. Bruna, K. Cho, J. Brehmer, G. Louppe et al., *Neural Message Passing for Jet Physics*, 2017.

- [30] X. Ju et al., *Graph Neural Networks for Particle Reconstruction in High Energy Physics detectors*, 3, 2020. 2003.11603.
- [31] J. Arjona Martínez, O. Cerri, M. Pierini, M. Spiropulu and J.-R. Vlimant, *Pileup mitigation at the Large Hadron Collider with graph neural networks*, *Eur. Phys. J. Plus* **134** (2019) 333, [1810.07988].
- [32] E. A. Moreno, O. Cerri, J. M. Duarte, H. B. Newman, T. Q. Nguyen, A. Periwai et al., *JEDI-net: a jet identification algorithm based on interaction networks*, *Eur. Phys. J. C* **80** (2020) 58, [1908.05318].
- [33] S. R. Qasim, J. Kieseler, Y. Iiyama and M. Pierini, *Learning representations of irregular particle-detector geometry with distance-weighted graph networks*, *Eur. Phys. J. C* **79** (2019) 608, [1902.07987].
- [34] A. Chakraborty, S. H. Lim and M. M. Nojiri, *Interpretable deep learning for two-prong jet classification with jet spectra*, *JHEP* **19** (2020) 135, [1904.02092].
- [35] A. Chakraborty, S. H. Lim, M. M. Nojiri and M. Takeuchi, *Neural Network-based Top Tagger with Two-Point Energy Correlations and Geometry of Soft Emissions*, 2003.11787.
- [36] M. Abdughani, D. Wang, L. Wu, J. M. Yang and J. Zhao, *Probing triple Higgs coupling with machine learning at the LHC*, 2005.11086.
- [37] E. Bernreuther, T. Finke, F. Kahlhoefer, M. Krämer and A. Mück, *Casting a graph net to catch dark showers*, 2006.08639.
- [38] P. T. Komiske, E. M. Metodiev and J. Thaler, *Energy Flow Networks: Deep Sets for Particle Jets*, *JHEP* **01** (2019) 121, [1810.05165].
- [39] H. Qu and L. Gouskos, *ParticleNet: Jet Tagging via Particle Clouds*, *Phys. Rev. D* **101** (2020) 056019, [1902.08570].
- [40] K. Datta, A. Larkoski and B. Nachman, *Automating the Construction of Jet Observables with Machine Learning*, 1902.07180.
- [41] K. Datta and A. Larkoski, *How Much Information is in a Jet?*, *JHEP* **06** (2017) 073, [1704.08249].
- [42] K. Datta and A. J. Larkoski, *Novel Jet Observables from Machine Learning*, *JHEP* **03** (2018) 086, [1710.01305].
- [43] P. T. Komiske, E. M. Metodiev and J. Thaler, *Energy flow polynomials: A complete linear basis for jet substructure*, *JHEP* **04** (2018) 013, [1712.07124].
- [44] A. Butter, G. Kasieczka, T. Plehn and M. Russell, *Deep-learned Top Tagging with a Lorentz Layer*, *SciPost Phys.* **5** (2018) 028, [1707.08966].

- [45] CMS collaboration, A. M. Sirunyan et al., *Identification of heavy, energetic, hadronically decaying particles using machine-learning techniques*, *JINST* **15** (2020) P06005, [2004.08262].
- [46] Y.-C. J. Chen, C.-W. Chiang, G. Cottin and D. Shih, *Boosted W and Z tagging with jet charge and deep learning*, *Phys. Rev. D* **101** (2020) 053001, [1908.08256].
- [47] K. Datta, A. Larkoski and B. Nachman, *Automating the Construction of Jet Observables with Machine Learning*, *Phys. Rev. D* **100** (2019) 095016, [1902.07180].
- [48] E. A. Moreno, T. Q. Nguyen, J.-R. Vlimant, O. Cerri, H. B. Newman, A. Periwai et al., *Interaction networks for the identification of boosted $H \rightarrow b\bar{b}$ decays*, 1909.12285.
- [49] M. Stoye, J. Kieseler, M. Verzetti, H. Qu, L. Gouskos, A. Stakia et al., *DeepJet: Generic physics object based jet multiclass classification for LHC experiments*, 2017.
- [50] Y.-T. Chien and R. Kunnawalkam Elayavalli, *Probing heavy ion collisions using quark and gluon jet substructure*, 1803.03589.
- [51] G. Kasieczka, N. Kiefer, T. Plehn and J. M. Thompson, *Quark-Gluon Tagging: Machine Learning vs Detector*, *SciPost Phys.* **6** (2019) 069, [1812.09223].
- [52] S. Diefenbacher, H. Frost, G. Kasieczka, T. Plehn and J. M. Thompson, *CapsNets Continuing the Convolutional Quest*, *SciPost Phys.* **8** (2020) 023, [1906.11265].
- [53] Y. Nakai, D. Shih and S. Thomas, *Strange Jet Tagging*, 2003.09517.
- [54] CMS collaboration, A. M. Sirunyan et al., *Identification of heavy-flavour jets with the CMS detector in pp collisions at 13 TeV*, 1712.07158.
- [55] J. Bielciková, R. K. Elayavalli, G. Ponimatkin, J. H. Putschke and J. Sivic, *Identifying Heavy-Flavor Jets Using Vectors of Locally Aggregated Descriptors*, 2005.01842.
- [56] P. Baldi, P. Sadowski and D. Whiteson, *Searching for Exotic Particles in High-Energy Physics with Deep Learning*, *Nature Commun.* **5** (2014) 4308, [1402.4735].
- [57] C. Collaboration, *A deep neural network to search for new long-lived particles decaying to jets*, *Machine Learning: Science and Technology* (2020) , [1912.12238].
- [58] J. Alimena, Y. Iiyama and J. Kieseler, *Fast convolutional neural networks for identifying long-lived particles in a high-granularity calorimeter*, 2004.10744.
- [59] L. De Oliveira, B. Nachman and M. Paganini, *Electromagnetic Showers Beyond Shower Shapes*, *Nucl. Instrum. Meth. A* **951** (2020) 162879, [1806.05667].
- [60] M. Paganini, L. de Oliveira and B. Nachman, *Survey of Machine Learning Techniques for High Energy Electromagnetic Shower Classification*, 2017.
- [61] B. Hooberman, A. Farbin, G. Khattak, V. Pacela, M. Pierini, J.-R. Vlimant et al.,

Calorimetry with Deep Learning: Particle Classification, Energy Regression, and Simulation for High-Energy Physics, 2017.

- [62] D. Belayneh et al., *Calorimetry with Deep Learning: Particle Simulation and Reconstruction for Collider Physics*, 1912.06794.
- [63] MICROBOONE collaboration, C. Adams et al., *Deep neural network for pixel-level electromagnetic particle identification in the MicroBooNE liquid argon time projection chamber*, *Phys. Rev.* **D99** (2019) 092001, [1808.07269].
- [64] A. Aurisano, A. Radovic, D. Rocco, A. Himmel, M. D. Messier, E. Niner et al., *A Convolutional Neural Network Neutrino Event Classifier*, *JINST* **11** (2016) P09001, [1604.01444].
- [65] MICROBOONE collaboration, R. Acciarri et al., *Convolutional Neural Networks Applied to Neutrino Events in a Liquid Argon Time Projection Chamber*, *JINST* **12** (2017) P03011, [1611.05531].
- [66] L. Hertel, L. Li, P. Baldi and J. Bian, *Convolutional Neural Networks for Electron Neutrino and Electron Shower Energy Reconstruction in the NOvA Detectors*, 2017.
- [67] KM3NET collaboration, S. Aiello et al., *Event reconstruction for KM3NeT/ORCA using convolutional neural networks*, 2004.08254.
- [68] C. Adams, K. Terao and T. Wongjirad, *PILArNet: Public Dataset for Particle Imaging Liquid Argon Detectors in High Energy Physics*, 2006.01993.
- [69] L. Dominé and K. Terao, *Point Proposal Network for Reconstructing 3D Particle Positions with Sub-Pixel Precision in Liquid Argon Time Projection Chambers*, 2006.14745.
- [70] S. Farrell, P. Calafiura, M. Mudigonda, Prabhat, D. Anderson, J. Bendavid et al., *Particle Track Reconstruction with Deep Learning*, 2017.
- [71] S. Farrell et al., *Novel deep learning methods for track reconstruction*, 10, 2018. 1810.06111.
- [72] S. Amrouche et al., *The Tracking Machine Learning challenge : Accuracy phase*, 1904.06778.
- [73] L.-G. Pang, K. Zhou, N. Su, H. Petersen, H. Stöcker and X.-N. Wang, *An EoS-meter of QCD transition from deep learning*, 1612.04262.
- [74] L. M. Dery, B. Nachman, F. Rubbo and A. Schwartzman, *Weakly Supervised Classification in High Energy Physics*, *JHEP* **05** (2017) 145, [1702.00414].
- [75] E. M. Metodiev, B. Nachman and J. Thaler, *Classification without labels: Learning from mixed samples in high energy physics*, *JHEP* **10** (2017) 174, [1708.02949].

- [76] J. H. Collins, K. Howe and B. Nachman, *Anomaly Detection for Resonant New Physics with Machine Learning*, *Phys. Rev. Lett.* **121** (2018) 241803, [1805.02664].
- [77] J. H. Collins, K. Howe and B. Nachman, *Extending the search for new resonances with machine learning*, *Phys. Rev.* **D99** (2019) 014038, [1902.02634].
- [78] M. Borisyak and N. Kazeev, *Machine Learning on data with sPlot background subtraction*, 1905.11719.
- [79] T. Cohen, M. Freytsis and B. Ostdiek, *(Machine) Learning to Do More with Less*, 1706.09451.
- [80] P. T. Komiske, E. M. Metodiev and J. Thaler, *An operational definition of quark and gluon jets*, *JHEP* **11** (2018) 059, [1809.01140].
- [81] E. M. Metodiev and J. Thaler, *Jet Topics: Disentangling Quarks and Gluons at Colliders*, *Phys. Rev. Lett.* **120** (2018) 241602, [1802.00008].
- [82] A. Collaboration, *Dijet resonance search with weak supervision using 13 TeV pp collisions in the ATLAS detector*, 2005.02983.
- [83] L. Mackey, B. Nachman, A. Schwartzman and C. Stansbury, *Fuzzy Jets*, *JHEP* **06** (2016) 010, [1509.02216].
- [84] P. T. Komiske, E. M. Metodiev and J. Thaler, *Metric Space of Collider Events*, *Phys. Rev. Lett.* **123** (2019) 041801, [1902.02346].
- [85] B. M. Dillon, D. A. Faroughy, J. F. Kamenik and M. Szewc, *Learning the latent structure of collider events*, 2005.12319.
- [86] B. M. Dillon, D. A. Faroughy and J. F. Kamenik, *Uncovering latent jet substructure*, *Phys. Rev.* **D100** (2019) 056002, [1904.04200].
- [87] G. C. Strong, *On the impact of modern deep-learning techniques to the performance and time-requirements of classification models in experimental high-energy physics*, 2002.01427.
- [88] V. V. Gligorov and M. Williams, *Efficient, reliable and fast high-level triggering using a bonsai boosted decision tree*, *JINST* **8** (2013) P02013, [1210.6861].
- [89] D. W. III, T. Q. Nguyen, D. Anderson, R. Castello, M. Pierini, M. Spiropulu et al., *Deep topology classifiers for a more efficient trigger selection at the LHC*, 2017.
- [90] D. Bourgeois, C. Fitzpatrick and S. Stahl, *Using holistic event information in the trigger*, 1808.00711.
- [91] J. Duarte et al., *Fast inference of deep neural networks in FPGAs for particle physics*, *JINST* **13** (2018) P07027, [1804.06913].
- [92] V. Loncar et al., *Compressing deep neural networks on FPGAs to binary and ternary precision with HLS4ML*, 2003.06308.

- [93] S. Summers et al., *Fast inference of Boosted Decision Trees in FPGAs for particle physics*, 2002.02534.
- [94] P. T. Komiske, E. M. Metodiev, B. Nachman and M. D. Schwartz, *Pileup Mitigation with Machine Learning (PUMML)*, *JHEP* **12** (2017) 051, [1707.08600].
- [95] S. Carrazza and F. A. Dreyer, *Jet grooming through reinforcement learning*, *Phys. Rev. D* **100** (2019) 014014, [1903.09644].
- [96] S. Cheong, A. Cukierman, B. Nachman, M. Safdari and A. Schwartzman, *Parametrizing the Detector Response with Neural Networks*, *JINST* **15** (2020) P01030, [1910.03773].
- [97] ATLAS COLLABORATION collaboration, *Simultaneous Jet Energy and Mass Calibrations with Neural Networks*, Tech. Rep. ATL-PHYS-PUB-2020-001, CERN, Geneva, Jan, 2020.
- [98] ATLAS COLLABORATION collaboration, *Generalized Numerical Inversion: A Neural Network Approach to Jet Calibration*, Tech. Rep. ATL-PHYS-PUB-2018-013, CERN, Geneva, Jul, 2018.
- [99] G. Kasieczka, M. Luchmann, F. Otterpohl and T. Plehn, *Per-Object Systematics using Deep-Learned Calibration*, 2003.11099.
- [100] CMS collaboration, A. M. Sirunyan et al., *A deep neural network for simultaneous estimation of b jet energy and resolution*, 1912.06046.
- [101] S. Caron, J. S. Kim, K. Rolbiecki, R. R. de Austri and B. Stienen, *The BSM-AI project: SUSY-AI-generalizing LHC limits on supersymmetry with machine learning*, *The European Physical Journal C* **77** (2017) 257.
- [102] G. Bertone, M. P. Deisenroth, J. S. Kim, S. Liem, R. Ruiz de Austri and M. Welling, *Accelerating the BSM interpretation of LHC data with machine learning*, 1611.02704.
- [103] F. Bishara and M. Montull, *(Machine) Learning Amplitudes for Faster Event Generation*, 1912.11055.
- [104] Y.-K. Lei, C. Liu and Z. Chen, *Numerical analysis of neutrino physics within a high scale supersymmetry model via machine learning*, 2006.01495.
- [105] G. Louppe, M. Kagan and K. Cranmer, *Learning to Pivot with Adversarial Networks*, 1611.01046.
- [106] J. Dolen, P. Harris, S. Marzani, S. Rappoccio and N. Tran, *Thinking outside the ROCs: Designing Decorrelated Taggers (DDT) for jet substructure*, *JHEP* **05** (2016) 156, [1603.00027].
- [107] I. Moutl, B. Nachman and D. Neill, *Convolved Substructure: Analytically Decorrelating Jet Substructure Observables*, *JHEP* **05** (2018) 002, [1710.06859].

- [108] J. Stevens and M. Williams, *uBoost: A boosting method for producing uniform selection efficiencies from multivariate classifiers*, *JINST* **8** (2013) P12013, [1305.7248].
- [109] C. Shimmmin, P. Sadowski, P. Baldi, E. Weik, D. Whiteson, E. Goul et al., *Decorrelated Jet Substructure Tagging using Adversarial Neural Networks*, 1703.03507.
- [110] L. Bradshaw, R. K. Mishra, A. Mitridate and B. Ostdiek, *Mass Agnostic Jet Taggers*, 1908.08959.
- [111] ATLAS collaboration, *Performance of mass-decorrelated jet substructure observables for hadronic two-body decay tagging in ATLAS*, *ATL-PHYS-PUB-2018-014* (2018) .
- [112] G. Kasieczka and D. Shih, *DisCo Fever: Robust Networks Through Distance Correlation*, 2001.05310.
- [113] L.-G. Xia, *QBDT, a new boosting decision tree method with systematical uncertainties into training for High Energy Physics*, *Nucl. Instrum. Meth.* **A930** (2019) 15–26, [1810.08387].
- [114] C. Englert, P. Galler, P. Harris and M. Spannowsky, *Machine Learning Uncertainties with Adversarial Neural Networks*, *Eur. Phys. J.* **C79** (2019) 4, [1807.08763].
- [115] S. Wunsch, S. Jörger, R. Wolf and G. Quast, *Reducing the dependence of the neural network function to systematic uncertainties in the input space*, 1907.11674.
- [116] A. Rogozhnikov, A. Bukva, V. V. Gligorov, A. Ustyuzhanin and M. Williams, *New approaches for boosting to uniformity*, *JINST* **10** (2015) T03002, [1410.4140].
- [117] J. M. Clavijo, P. Glaysheer and J. M. Katzy, *Adversarial domain adaptation to reduce sample bias of a high energy physics classifier*, 2005.00568.
- [118] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair et al., *Generative Adversarial Networks*, 1406.2661.
- [119] L. de Oliveira, M. Paganini and B. Nachman, *Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis*, 1701.05927.
- [120] M. Paganini, L. de Oliveira and B. Nachman, *Accelerating Science with Generative Adversarial Networks: An Application to 3D Particle Showers in Multilayer Calorimeters*, *Phys. Rev. Lett.* **120** (2018) 042003, [1705.02355].
- [121] M. Paganini, L. de Oliveira and B. Nachman, *CaloGAN : Simulating 3D high energy particle showers in multilayer electromagnetic calorimeters with generative adversarial networks*, *Phys. Rev.* **D97** (2018) 014021, [1712.10321].
- [122] S. Alonso-Monsalve and L. H. Whitehead, *Image-based model parameter optimization using Model-Assisted Generative Adversarial Networks*, 1812.00879.

- [123] A. Butter, T. Plehn and R. Winterhalder, *How to GAN Event Subtraction*, 1912.08824.
- [124] J. Arjona Martinez, T. Q. Nguyen, M. Pierini, M. Spiropulu and J.-R. Vlimant, *Particle Generative Adversarial Networks for full-event simulation at the LHC and their application to pileup description*, 2019. 1912.02748.
- [125] M. Bellagente, A. Butter, G. Kasieczka, T. Plehn and R. Winterhalder, *How to GAN away Detector Effects*, 1912.00477.
- [126] S. Vallecorsa, F. Carminati and G. Khattak, *3D convolutional GAN for fast simulation*, *Proceedings, 23rd International Conference on Computing in High Energy and Nuclear Physics (CHEP 2018): Sofia, Bulgaria, July 9-13, 2018* **214** (2019) 02010.
- [127] SHiP collaboration, C. Ahdida et al., *Fast simulation of muons produced at the SHiP experiment using Generative Adversarial Networks*, 1909.04451.
- [128] S. Carrazza and F. A. Dreyer, *Lund jet images from generative and cycle-consistent adversarial networks*, *Eur. Phys. J.* **C79** (2019) 979, [1909.01359].
- [129] A. Butter, T. Plehn and R. Winterhalder, *How to GAN LHC Events*, *SciPost Phys.* **7** (2019) 075, [1907.03764].
- [130] J. Lin, W. Bhimji and B. Nachman, *Machine Learning Templates for QCD Factorization in the Search for Physics Beyond the Standard Model*, *JHEP* **05** (2019) 181, [1903.02556].
- [131] R. Di Sipio, M. Fauci Giannelli, S. Ketabchi Haghighat and S. Palazzo, *DijetGAN: A Generative-Adversarial Network Approach for the Simulation of QCD Dijet Events at the LHC*, 1903.02433.
- [132] B. Hashemi, N. Amin, K. Datta, D. Olivito and M. Pierini, *LHC analysis-specific datasets with Generative Adversarial Networks*, 1901.05282.
- [133] V. Chekalina, E. Orlova, F. Ratnikov, D. Ulyanov, A. Ustyuzhanin and E. Zakharov, *Generative Models for Fast Calorimeter Simulation.LHCb case*, 2018. 1812.01319.
- [134] ATLAS collaboration, *Deep generative models for fast shower simulation in ATLAS*, *ATL-SOFT-PUB-2018-001* (Jul, 2018) .
- [135] K. Zhou, G. Endrodi, L.-G. Pang and H. Stocker, *Regressive and generative neural networks for scalar field theory*, *Phys. Rev.* **D100** (2019) 011501, [1810.12879].
- [136] F. Carminati, A. Gheata, G. Khattak, P. Mendez Lorenzo, S. Sharan and S. Vallecorsa, *Three dimensional Generative Adversarial Networks for fast simulation*, *Proceedings, 18th International Workshop on Advanced Computing and Analysis Techniques in Physics Research (ACAT 2017): Seattle, WA, USA, August 21-25, 2017* **1085** (2018) 032016.

- [137] S. Vallecorsa, *Generative models for fast simulation, Proceedings, 18th International Workshop on Advanced Computing and Analysis Techniques in Physics Research (ACAT 2017): Seattle, WA, USA, August 21-25, 2017* **1085** (2018) 022005.
- [138] K. Datta, D. Kar and D. Roy, *Unfolding with Generative Adversarial Networks*, 1806.00433.
- [139] P. Musella and F. Pandolfi, *Fast and Accurate Simulation of Particle Detectors Using Generative Adversarial Networks*, *Comput. Softw. Big Sci.* **2** (2018) 8, [1805.00850].
- [140] M. Erdmann, L. Geiger, J. Glombitza and D. Schmidt, *Generating and refining particle detector simulations using the Wasserstein distance in adversarial networks*, *Comput. Softw. Big Sci.* **2** (2018) 4, [1802.03325].
- [141] K. Deja, T. Trzcinski and u. Graczykowski, *Generative models for fast cluster simulations in the TPC for the ALICE experiment, Proceedings, 23rd International Conference on Computing in High Energy and Nuclear Physics (CHEP 2018): Sofia, Bulgaria, July 9-13, 2018* **214** (2019) 06003.
- [142] D. Derkach, N. Kazeev, F. Ratnikov, A. Ustyuzhanin and A. Volokhova, *Cherenkov Detectors Fast Simulation Using Neural Networks*, 2019. 1903.11788. DOI.
- [143] H. Erbin and S. Krippendorff, *GANs for generating EFT models*, 1809.02612.
- [144] M. Erdmann, J. Glombitza and T. Quast, *Precise simulation of electromagnetic calorimeter showers using a Wasserstein Generative Adversarial Network*, *Comput. Softw. Big Sci.* **3** (2019) 4, [1807.01954].
- [145] J. M. Urban and J. M. Pawlowski, *Reducing Autocorrelation Times in Lattice Simulations with Generative Adversarial Networks*, 1811.03533.
- [146] L. de Oliveira, M. Paganini and B. Nachman, *Tips and Tricks for Training GANs with Physics Constraints*, 2017.
- [147] L. de Oliveira, M. Paganini and B. Nachman, *Controlling Physical Attributes in GAN-Accelerated Simulation of Electromagnetic Calorimeters*, *J. Phys. Conf. Ser.* **1085** (2018) 042017, [1711.08813].
- [148] S. Farrell, W. Bhimji, T. Kurth, M. Mustafa, D. Bard, Z. Lukic et al., *Next Generation Generative Neural Networks for HEP*, *EPJ Web Conf.* **214** (2019) 09005.
- [149] E. Buhmann, S. Diefenbacher, E. Eren, F. Gaede, G. Kasieczka, A. Korol et al., *Getting High: High Fidelity Simulation of High Granularity Calorimeters with High Speed*, 2005.05334.
- [150] J. W. Monk, *Deep Learning as a Parton Shower*, 1807.03685.
- [151] A. Andreassen, I. Feige, C. Frye and M. D. Schwartz, *JUNIPR: a Framework for Unsupervised Machine Learning in Particle Physics*, 1804.09720.

- [152] A. Andreassen, I. Feige, C. Frye and M. D. Schwartz, *Binary JUNIPR: an interpretable probabilistic model for discrimination*, *Phys. Rev. Lett.* **123** (2019) 182001, [1906.10137].
- [153] D. Rezende and S. Mohamed, *Variational inference with normalizing flows*, vol. 37 of *Proceedings of Machine Learning Research*, (Lille, France), pp. 1530–1538, PMLR, 07–09 Jul, 2015.
- [154] M. S. Albergo, G. Kanwar and P. E. Shanahan, *Flow-based generative models for Markov chain Monte Carlo in lattice field theory*, *Phys. Rev.* **D100** (2019) 034515, [1904.12072].
- [155] G. Kanwar, M. S. Albergo, D. Boyda, K. Cranmer, D. C. Hackett, S. Racanière et al., *Equivariant flow-based sampling for lattice gauge theory*, 2003.06413.
- [156] J. Brehmer and K. Cranmer, *Flows for simultaneous manifold learning and density estimation*, 2003.13913.
- [157] E. Bothmann, T. Janßen, M. Knobbe, T. Schmale and S. Schumann, *Exploring phase space with Neural Importance Sampling*, 2001.05478.
- [158] C. Gao, S. Höche, J. Isaacson, C. Krause and H. Schulz, *Event Generation with Normalizing Flows*, *Phys. Rev. D* **101** (2020) 076002, [2001.10028].
- [159] C. Gao, J. Isaacson and C. Krause, *i-flow: High-Dimensional Integration and Sampling with Normalizing Flows*, 2001.05486.
- [160] B. Nachman and D. Shih, *Anomaly Detection with Density Estimation*, *Phys. Rev. D* **101** (2020) 075042, [2001.04990].
- [161] J. Bendavid, *Efficient Monte Carlo Integration Using Boosted Decision Trees and Generative Deep Neural Networks*, 1707.00028.
- [162] M. D. Klimek and M. Perelstein, *Neural Network-Based Approach to Phase Space Integration*, 1810.11509.
- [163] S. Carrazza and J. M. Cruz-Martinez, *VegasFlow: accelerating Monte Carlo simulation across multiple hardware platforms*, 2002.12921.
- [164] M. Frate, K. Cranmer, S. Kalia, A. Vandenberg-Rodes and D. Whiteson, *Modeling Smooth Backgrounds and Generic Localized Signals with Gaussian Processes*, 1709.05681.
- [165] R. T. D’Agnolo and A. Wulzer, *Learning New Physics from a Machine*, *Phys. Rev.* **D99** (2019) 015014, [1806.02350].
- [166] R. T. D’Agnolo, G. Grosso, M. Pierini, A. Wulzer and M. Zanetti, *Learning Multivariate New Physics*, 1912.12155.

- [167] M. Farina, Y. Nakai and D. Shih, *Searching for New Physics with Deep Autoencoders*, 1808.08992.
- [168] T. Heimgel, G. Kasieczka, T. Plehn and J. M. Thompson, *QCD or What?*, *SciPost Phys.* **6** (2019) 030, [1808.08979].
- [169] T. S. Roy and A. H. Vijay, *A robust anomaly finder based on autoencoder*, 1903.02032.
- [170] O. Cerri, T. Q. Nguyen, M. Pierini, M. Spiropulu and J.-R. Vlimant, *Variational Autoencoders for New Physics Mining at the Large Hadron Collider*, *JHEP* **05** (2019) 036, [1811.10276].
- [171] A. Blance, M. Spannowsky and P. Waite, *Adversarially-trained autoencoders for robust unsupervised new physics searches*, *JHEP* **10** (2019) 047, [1905.10384].
- [172] J. Hajer, Y.-Y. Li, T. Liu and H. Wang, *Novelty Detection Meets Collider Physics*, 1807.10261.
- [173] A. De Simone and T. Jacques, *Guiding New Physics Searches with Unsupervised Learning*, *Eur. Phys. J.* **C79** (2019) 289, [1807.06038].
- [174] A. Mullin, H. Pacey, M. Parker, M. White and S. Williams, *Does SUSY have friends? A new approach for LHC event analysis*, 1912.10625.
- [175] G. M. Alessandro Casa, *Nonparametric semisupervised classification for signal detection in high energy physics*, 1809.02977.
- [176] A. Andreassen, B. Nachman and D. Shih, *Simulation Assisted Likelihood-free Anomaly Detection*, *Phys. Rev. D* **101** (2020) 095004, [2001.05001].
- [177] J. A. Aguilar-Saavedra, J. H. Collins and R. K. Mishra, *A generic anti-QCD jet tagger*, *JHEP* **11** (2017) 163, [1709.01087].
- [178] M. Romão Crispim, N. Castro, R. Pedro and T. Vale, *Transferability of Deep Learning Models in Searches for New Physics at Colliders*, *Phys. Rev. D* **101** (2020) 035042, [1912.04220].
- [179] M. C. Romao, N. Castro, J. Milhano, R. Pedro and T. Vale, *Use of a Generalized Energy Mover’s Distance in the Search for Rare Phenomena at Colliders*, 2004.09360.
- [180] O. Knapp, G. Dissertori, O. Cerri, T. Q. Nguyen, J.-R. Vlimant and M. Pierini, *Adversarially Learned Anomaly Detection on CMS Open Data: re-discovering the top quark*, 2005.01598.
- [181] K. Cranmer, J. Brehmer and G. Louppe, *The frontier of simulation-based inference*, 11, 2019. 1911.01429.
- [182] A. Andreassen and B. Nachman, *Neural Networks for Full Phase-space Reweighting and Parameter Tuning*, *Phys. Rev. D* **101** (2020) 091901, [1907.08209].

- [183] M. Stoye, J. Brehmer, G. Louppe, J. Pavez and K. Cranmer, *Likelihood-free inference with an improved cross-entropy estimator*, 1808.00973.
- [184] J. Hollingsworth and D. Whiteson, *Resonance Searches with Machine Learned Likelihood Ratios*, 2002.04699.
- [185] J. Brehmer, K. Cranmer, G. Louppe and J. Pavez, *Constraining Effective Field Theories with Machine Learning*, 1805.00013.
- [186] J. Brehmer, K. Cranmer, G. Louppe and J. Pavez, *A Guide to Constraining Effective Field Theories with Machine Learning*, 1805.00020.
- [187] J. Brehmer, F. Kling, I. Espejo and K. Cranmer, *MadMiner: Machine learning-based inference for particle physics*, *Comput. Softw. Big Sci.* **4** (2020) 3, [1907.10621].
- [188] J. Brehmer, G. Louppe, J. Pavez and K. Cranmer, *Mining gold from implicit models to improve likelihood-free inference*, *Proc. Nat. Acad. Sci.* (2020) 201915980, [1805.12244].
- [189] A. Andreassen, P. T. Komiske, E. M. Metodiev, B. Nachman and J. Thaler, *OmniFold: A Method to Simultaneously Unfold All Observables*, *Phys. Rev. Lett.* **124** (2020) 182001, [1911.09107].
- [190] N. D. Gagunashvili, *Machine learning approach to inverse problem and unfolding procedure*, 1004.2006.
- [191] A. Glazov, *Machine learning as an instrument for data unfolding*, 1712.01814.
- [192] D. Martschei, M. Feindt, S. Honc and J. Wagner-Kuhr, *Advanced event reweighting using multivariate analysis*, *J. Phys. Conf. Ser.* **368** (2012) 012028.
- [193] L. Lindemann and G. Zech, *Unfolding by weighting Monte Carlo events*, *Nucl. Instrum. Meth. A* **354** (1995) 516–521.
- [194] G. Zech and B. Aslan, *Binning-Free Unfolding Based on Monte Carlo Migration*, 2003.
- [195] M. Bellagente, A. Butter, G. Kasieczka, T. Plehn, A. Rousselot and R. Winterhalder, *Invertible Networks or Partons to Detector and Back Again*, 2006.06685.
- [196] A. Rogozhnikov, *Reweighting with Boosted Decision Trees*, *Proceedings, 17th International Workshop on Advanced Computing and Analysis Techniques in Physics Research (ACAT 2016): Valparaiso, Chile, January 18-22, 2016* **762** (2016) 012036, [1608.05806].
- [197] S. Chang, T. Cohen and B. Ostdiek, *What is the Machine Learning?*, *Phys. Rev.* **D97** (2018) 056009, [1709.10106].
- [198] B. Nachman, *A guide for deploying Deep Learning in LHC searches: How to achieve optimality and account for uncertainty*, 1909.03081.
- [199] B. Nachman and C. Shimmin, *AI Safety for High Energy Physics*, 1910.08606.

- [200] V. Estrade, C. Germain, I. Guyon and D. Rousseau, *Adversarial learning to eliminate systematic errors: a case study in High Energy Physics*, 2017.
- [201] S. Caron, T. Heskes, S. Otten and B. Stienen, *Constraining the Parameters of High-Dimensional Models with Active Learning*, *Eur. Phys. J. C* **79** (2019) 944, [1905.08628].
- [202] S. Bollweg, M. Haußmann, G. Kasieczka, M. Luchmann, T. Plehn and J. Thompson, *Deep-Learning Jets with Uncertainties and More*, *SciPost Phys.* **8** (2020) 006, [1904.10004].
- [203] P. De Castro and T. Dorigo, *INFERNO: Inference-Aware Neural Optimisation*, *Comput. Phys. Commun.* **244** (2019) 170–179, [1806.04743].
- [204] S. Wunsch, S. Jörger, R. Wolf and G. Quast, *Optimal statistical inference in the presence of systematic uncertainties using neural network optimization based on binned Poisson likelihoods with nuisance parameters*, 2003.07186.
- [205] ATLAS collaboration, G. Aad et al., *Search for non-resonant Higgs boson pair production in the $b\bar{b}\ell\nu\ell\nu$ final state with the ATLAS detector in pp collisions at $\sqrt{s} = 13$ TeV*, *Phys. Lett. B* **801** (2020) 135145, [1908.06765].
- [206] ATLAS collaboration, G. Aad et al., *Search for Higgs boson decays into a Z boson and a light hadronically decaying resonance using 13 TeV pp collision data from the ATLAS detector*, 2004.01678.