A Living Review of Machine Learning for Particle Physics

ABSTRACT: Modern machine learning techniques, including deep learning, are 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[1] before you write your next paper. You can simply download the .bib file to get all of the latest references. Please consider citing Ref. [1] when referring to this living review.

- **Reviews**
  Below are links to many (static) general and specialized reviews. The third bullet contains links to classic papers that applied shallow learning methods many decades before the deep learning revolution.

  – Modern reviews [2–7]
  – Specialized reviews [8–21]
  – Classical papers [22, 23]

- **Classification**
  Given a feature space $x \in \mathbb{R}^n$, a binary classifier is a function $f : \mathbb{R}^n \rightarrow [0,1]$, where 0 corresponds to features that are more characteristic of the zeroth class (e.g. background) and 1 correspond to features that are more characteristic of the one class (e.g. signal). Typically, f will be a function specified by some parameters w (e.g. weights and biases of a neural network) that are determined by minimizing a loss of the form $L[f] = \sum_i \ell(f(x_i), y_i)$, where $y_i \in \{0,1\}$ are labels. The function ℓ is smaller when $f(x_i)$ and y_i are closer. Two common loss functions are the mean squared error $\ell(x,y) = (x-y)^2$ and the binary cross entropy $\ell(x,y) = y \log(x) + (1-y) \log(1-x)$. Exactly what 'more characteristic of' means depends on the loss function used to determine f. It is also possible to make a multi-class classifier. A common strategy for the multi-class case is to represent each class as a different basis vector in $\mathbb{R}^{n_{classes}}$ and then $f(x) \in [0,1]^{n_{classes}}$. In this case, $f(x)$ is usually restricted to have its $n_{classes}$ components sum to one and the loss function is typically the cross entropy $\ell(x,y) = \sum_{classes\ i} y_i \log(x)$.

---

[1]See https://github.com/iml-wg/HEPML-LivingReview.

– **Parameterized classifiers** [24–26].

A classifier that is conditioned on model parameters $f(x|\theta)$ is called a parameterized classifier.

– **Representations**

There is no unique way to represent high energy physics data. It is often natural to encode x as an image or another one of the structures listed below.

  ∗ **Jet images** [27–42]

  Jets are collimated sprays of particles. They have a complex radiation pattern and such, have been a prototypical example for many machine learning studies. See the next item for a specific description about images.

  ∗ **Event images** [32, 43–47]

  A grayscale image is a regular grid with a scalar value at each grid point. 'Color' images have a fixed-length vector at each grid point. Many detectors are analogous to digital cameras and thus images are a natural representation. In other cases, images can be created by discretizing. Convolutional neural networks are natural tools for processing image data. One downside of the image representation is that high energy physics data tend to be sparse, unlike natural images.

  ∗ **Sequences** [43, 48–50]

  Data that have a variable with a particular order may be represented as a sequence. Recurrent neural networks are natural tools for processing sequence data.

  ∗ **Trees** [51, 52]

  Recursive neural networks are natural tools for processing data in a tree structure.

  ∗ **Graphs** [10, 53–71]

  A graph is a collection of nodes and edges. Graph neural networks are natural tools for processing data in a tree structure.

  ∗ **Sets (point clouds)** [41, 72–78]

  A point cloud is a (potentially variable-size) set of points in space. Sets are distinguished from sequences in that there is no particular order (i.e. permutation invariance). Sets can also be viewed as graphs without edges and so graph methods that can parse variable-length inputs may also be appropriate for set learning, although there are other methods as well.

  ∗ **Physics-inspired basis** [79–83]

This is a catch-all category for learning using other representations that use some sort of manual or automated physics-preprocessing.

– Targets

    * *W/Z* **tagging** [30, 34, 51, 63, 69, 84, 85]
    Boosted, hadronically decaying W and Z bosons form jets that are distinguished from generic quark and gluon jets by their mass near the boson mass and their two-prong substructure.

    * *H → b̄b* [32, 46, 58, 66, 84, 86–89]
    Due to the fidelity of b-tagging, boosted, hadronically decaying Higgs bosons (predominantly decaying to b̄b) has unique challenged and opportunities compared with W/Z tagging.

    * **quarks and gluons** [31, 35, 40, 52, 56, 69, 90–94]
    Quark jets tend to be narrower and have fewer particles than gluon jets. This classification task has been a benchmark for many new machine learning models.

    * **top quark** tagging [8, 29, 36, 37, 59, 69, 83, 90, 95–98]
    Boosted top quarks form jets that have a three-prong substructure ($t \rightarrow Wb, W \rightarrow q\bar{q}$).

    * **strange jets** [99–101]
    Strange quarks have a very similar fragmentation to generic quark and gluon jets, so this is a particularly challenging task.

    * *b*-**tagging** [48, 49, 102, 103]
    Due to their long (but not too long) lifetime, the B-hadron lifetime is macroscopic and b-jet tagging has been one of the earliest adapters of modern machine learning tools.

    * **Flavor physics** [104]
    This category is for studies related to exclusive particle decays, especially with bottom and charm hadrons.

    * **BSM particles and models** [58, 61, 86, 105–115]
    There are many proposals to train classifiers to enhance the presence of particular new physics models.

    * **Particle identification** [57, 116–120]
    This is a generic category for direct particle identification and categorization using various detector technologies. Direct means that the particle directly interacts with the detector (in contrast with b-tagging).

∗ **Neutrino Detectors** [11, 65, 70, 121–136]
Neutrino detectors are very large in order to have a sizable rate of neutrino detection. The entire neutrino interaction can be characterized to distinguish different neutrino flavors.

∗ **Direct Dark Matter Detectors** [137–139]
Dark matter detectors are similar to neutrino detectors, but aim to achieve 'zero' background.

∗ **Cosmology, Astro Particle, and Cosmic Ray physics** [68, 140–147]
Machine learning is often used in astrophysics and cosmology in different ways than terrestrial particle physics experiments due to a general divide between Bayesian and Frequentist statistics. However, there are many similar tasks and a growing number of proposals designed for one domain that apply to the other.

∗ **Tracking** [50, 54, 64, 75, 148–154]
Charged particle tracking is a challenging pattern recognition task. This category is for various classification tasks associated with tracking, such as seed selection.

∗ **Heavy ions** [42, 47, 91, 155]
Many tools in high energy nuclear physics are similar to high energy particle physics. The physics target of these studies are to understand collective properties of the strong force.

– **Learning strategies**
There is no unique way to train a classifier and designing an effective learning strategy is often one of the biggest challenges for achieving optimality.

∗ **Hyperparameters** [156]
In addition to learnable weights w, classifiers have a number of non-differentiable parameters like the number of layers in a neural network. These parameters are called hyperparameters.

∗ **Weak supervision** [33, 94, 157–168]
For supervised learning, the labels y_i are known. In the case that the labels are noisy or only known with some uncertainty, then the learning is called weak supervision. Semi-supervised learning is the related case where labels are known for only a fraction of the training examples.

∗ **Unsupervised** [169–174]
When no labels are provided, the learning is called unsupervised.

* **Reinforcement Learning** [175–177]
  Instead of learning to distinguish different types of examples, the goal of reinforcement learning is to learn a strategy (policy). The prototypical example of reinforcement learning in learning a strategy to play video games using some kind of score as a feedback during the learning.

* **Quantum Machine Learning** [21, 134, 178–183]
  Quantum computers are based on unitary operations applied to quantum states. These states live in a vast Hilbert space which may have a usefully large information capacity for machine learning.

* **Feature ranking** [184]
  It is often useful to take a set of input features and rank them based on their usefulness.

* **Attention** [50]
  This is an ML tool for helping the network to focus on particularly useful features.

* **Regularization** [185]
  This is a term referring to any learning strategy that improves the robustness of a classifier to statistical fluctuations in the data and in the model initialization.

– **Fast inference / deployment**
  There are many practical issues that can be critical for the actual application of machine learning models.

* **Software** [43, 107, 144, 186–189]
  Strategies for efficient inference for a given hardware architecture.

* **Hardware/firmware** [62, 67, 190–198]
  Various accelerators have been studied for fast inference that is very important for latency-limited applications like the trigger at collider experiments.

* **Deployment** [199]
  This category is for the deployment of machine learning interfaces, such as in the cloud.

- **Regression**
  In contrast to classification, the goal of regression is to learn a function $f : \mathbb{R}^n \to \mathbb{R}^m$ for input features $x \in \mathbb{R}^n$ and target features $y \in \mathbb{R}^m$. The learning setup is very similar to classification, where the network architectures and loss functions may need to be tweaked. For example, the mean squared error is the most common

loss function for regression, but the network output is no longer restricted to be between 0 and 1.

– **Pileup** [44, 55, 175, 200]
A given bunch crossing at the LHC will have many nearly simultaneous proton-proton collisions. Only one of those is usually interesting and the rest introduce a source of noise (pileup) that must be mitigating for precise final state reconstruction.

– **Calibration** [42, 118, 201–206]
The goal of calibration is to remove the bias (and reduce variance if possible) from detector (or related) effects.

– **Recasting** [207–209]
Even though an experimental analysis may provide a single model-dependent interpretation of the result, the results are likely to have important implications for a variety of other models. Recasting is the task of taking a result and interpreting it in the context of a model that was not used for the original analysis.

– **Matrix elements** [210–212]
Regression methods can be used as surrogate models for functions that are too slow to evaluate. One important class of functions are matrix elements, which form the core component of cross section calculations in quantum field theory.

– **Parameter estimation** [213–215]
The target features could be parameters of a model, which can be learned directly through a regression setup. Other forms of inference are described in later sections (which could also be viewed as regression).

– **Parton Distribution Functions (and related)** [197, 216, 217]
Various machine learning models can provide flexible function approximators, which can be useful for modeling functions that cannot be determined easily from first principles such as parton distribution functions.

– **Lattice Gauge Theory** [218, 219]
Lattice methods offer a complementary approach to perturbation theory. A key challenge is to create approaches that respect the local gauge symmetry (equivariant networks).

• **Decorrelation methods** [106, 220–234]
It it sometimes the case that a classification or regression model needs to be

independent of a set of features (usually a mass-like variable) in order to estimate the background or otherwise reduce the uncertainty. These techniques are related to what the machine learning literature calls model 'fairness'.

- **Generative models / density estimation**
  The goal of generative modeling is to learn (explicitly or implicitly) a probability density $p(x)$ for the features $x \in \mathbb{R}^n$. This task is usually unsupervised (no labels).

  - **GANs**: [118, 119, 235–271]
    Generative Adversarial Networks [272] learn $p(x)$ implicitly through the minimax optimization of two networks: one that maps noise to structure $G(z)$ and one a classifier (called the discriminator) that learns to distinguish examples generated from $G(z)$ and those generated from the target process. When the discriminator is maximally 'confused', then the generator is effectively mimicking $p(x)$.

  - **Autoencoders** [174, 250, 273–275]
    An autoencoder consists of two functions: one that maps x into a latent space z (encoder) and a second one that maps the latent space back into the original space (decoder). The encoder and decoder are simultaneously trained so that their composition is nearly the identity. When the latent space has a well-defined probability density (as in variational autoencoders), then one can sample from the autoencoder by applying the detector to a randomly chosen element of the latent space.

  - **Normalizing flows** [218, 276–284]
    Normalizing flows [285] learn $p(x)$ explicitly by starting with a simple probability density and then applyinga series of bijective transformations with tractable Jacobians.

  - **Physics-inspired** [271, 286–288]
    A variety of methods have been proposed to use machine learning tools (e.g. neural networks) combined with physical components.

  - **Mixture Models** [289]
    A mixture model is a superposition of simple probability densities. For example, a Gaussian mixture model is a sum of normal probability densities. Mixture density networks are mixture models where the coefficients in front of the constituent densities as well as the density parameters (e.g. mean and variances of Gaussians) are parameterized by neural networks.

– **Phase space generation** [278–280, 290–296]

Monte Carlo event generators integrate over a phase space that needs to be generated efficiently and this can be aided by machine learning methods.

– **Gaussian processes** [208, 211, 297]

These are non-parametric tools for modeling the 'time'-dependence of a random variable. The 'time' need not be actual time - for instance, one can use Gaussian processes to model the energy dependence of some probability density.

- **Anomaly detection** [159, 160, 165, 166, 171, 172, 274, 281, 298–326]

The goal of anomaly detection is to identify abnormal events. The abnormal events could be from physics beyond the Standard Model or from faults in a detector. While nearly all searches for new physics are technically anomaly detection, this category is for methods that are mode-independent (broadly defined). Anomalies in high energy physics tend to manifest as over-densities in phase space (often called 'population anomalies') in contrast to off-manifold anomalies where you can flag individual examples as anomalous.

- **Simulation-based ('likelihood-free') Inference**

Likelihood-based inference is the case where $p(x|\theta)$ is known and θ can be determined by maximizing the probability of the data. In high energy physics, $p(x|\theta)$ is often not known analytically, but it is often possible to sample from the density implicitly using simulations.

– **Parameter estimation** [25, 26, 284, 327–336]

This can also be viewed as a regression problem, but there the goal is typically to do maximum likelihood estimation in contrast to directly minimizing the mean squared error between a function and the target.

– **Unfolding** [174, 241, 254, 337–344]

This is the task of removing detector distortions. In contrast to parameter estimation, the goal is not to infer model parameters, but instead, the undistorted phase space probability density. This is often also called deconvlution.

– **Domain adaptation** [25, 267, 327, 345]

Morphing simulations to look like data is a form of domain adaptation.

– **BSM** [309, 312, 329–333]

This category is for parameter estimation when the parameter is the signal strength of new physics.

- **Uncertainty Quantification**
  Estimating and mitigating uncertainty is essential for the successful deployment of machine learning methods in high energy physics.

  - **Interpretability** [30, 95, 346, 347]
    Machine learning methods that are interpretable maybe more robust and thus less susceptible to various sources of uncertainty.

  - **Estimation** [34, 348, 349]
    A first step in reducing uncertainties is estimating their size.

  - **Mitigation** [185, 220, 229, 350]
    This category is for proposals to reduce uncertainty.

  - **Uncertainty-aware inference** [351–354]
    The usual path for inference is that a machine learning method is trained for a nominal setup. Uncertainties are then propagated in the usual way. This is suboptimal and so there are multiple proposals for incorporating uncertainties into the learning to get as close to making the final statistical test the target of the machine learning as possible.

- **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 [165, 355–357].

References

[1] M. Feickert and B. Nachman, *A Living Review of Machine Learning for Particle Physics*, 2102.02770. 1

[2] 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]. 1

[3] D. Guest, K. Cranmer and D. Whiteson, *Deep Learning and its Application to LHC Physics*, 1806.11484.

[4] K. Albertsson et al., *Machine Learning in High Energy Physics Community White Paper*, 1807.02876.

[5] 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.

[6] 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].

[7] D. Bourilkov, *Machine and Deep Learning Applications in Particle Physics, Int. J. Mod. Phys. A* **34** (2020) 1930019, [1912.08245]. 1

[8] A. Butter et al., *The Machine Learning Landscape of Top Taggers, SciPost Phys.* **7** (2019) 014, [1902.09914]. 1, 3

[9] T. Dorigo and P. de Castro, *Dealing with Nuisance Parameters using Machine Learning in High Energy Physics: a Review*, 2007.09121.

[10] J. Shlomi, P. Battaglia and J.-R. Vlimant, *Graph neural networks in particle physics, Machine Learning: Science and Technology* **2** (Jan, 2021) 021001, [2007.13681]. 2

[11] F. Psihas, M. Groh, C. Tunnell and K. Warburton, *A Review on Machine Learning for Neutrino Experiments*, 2008.01242. 4

[12] A. Butter and T. Plehn, *Generative Networks for LHC events*, 2008.08558.

[13] S. Forte and S. Carrazza, *Parton distribution functions*, 2008.12305.

[14] J. Brehmer and K. Cranmer, *Simulation-based inference methods for particle physics*, 2010.06439.

[15] B. Nachman, *Anomaly Detection for Physics Analysis and Less than Supervised Learning*, 2010.14554.

[16] J. Duarte and J.-R. Vlimant, *Graph Neural Networks for Particle Tracking and Reconstruction*, 2012.01249.

[17] J.-R. Vlimant and J. Yin, *Distributed Training and Optimization Of Neural Networks*, 2012.01839.

[18] K. Cranmer, J. Brehmer and G. Louppe, *The frontier of simulation-based inference*, 1911.01429.

[19] D. Rousseau and A. Ustyuzhanin, *Machine Learning scientific competitions and datasets*, 2012.08520.

[20] M. Kagan, *Image-Based Jet Analysis*, 2012.09719.

[21] W. Guan, G. Perdue, A. Pesah, M. Schuld, K. Terashi, S. Vallecorsa et al., *Quantum Machine Learning in High Energy Physics*, 2005.08582. 1, 5

[22] B. H. Denby, *Neural Networks and Cellular Automata in Experimental High-energy Physics*, *Comput. Phys. Commun.* **49** (1988) 429–448. 1

[23] L. Lonnblad, C. Peterson and T. Rognvaldsson, *Finding Gluon Jets With a Neural Trigger*, *Phys. Rev. Lett.* **65** (1990) 1321–1324. 1

[24] P. Baldi, K. Cranmer, T. Faucett, P. Sadowski and D. Whiteson, *Parameterized neural networks for high-energy physics*, *Eur. Phys. J.* **C76** (2016) 235, [1601.07913]. 2

[25] K. Cranmer, J. Pavez and G. Louppe, *Approximating Likelihood Ratios with Calibrated Discriminative Classifiers*, 1506.02169. 8

[26] B. Nachman and J. Thaler, *E Pluribus Unum Ex Machina: Learning from Many Collider Events at Once*, 2101.07263. 2, 8

[27] J. Pumplin, *How to tell quark jets from gluon jets*, *Phys. Rev. D* **44** (1991) 2025–2032. 2

[28] J. Cogan, M. Kagan, E. Strauss and A. Schwarztman, *Jet-Images: Computer Vision Inspired Techniques for Jet Tagging*, *JHEP* **02** (2015) 118, [1407.5675].

[29] 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]. 3

[30] L. de Oliveira, M. Kagan, L. Mackey, B. Nachman and A. Schwartzman, *Jet-images — deep learning edition*, *JHEP* **07** (2016) 069, [1511.05190]. 3, 9

[31] 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. 3

[32] J. Lin, M. Freytsis, I. Moult and B. Nachman, *Boosting $H \to b\bar{b}$ with Machine Learning*, *JHEP* **10** (2018) 101, [1807.10768]. 2, 3

[33] 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]. 4

[34] 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]. 3, 9

[35] 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]. 3

[36] G. Kasieczka, T. Plehn, M. Russell and T. Schell, *Deep-learning Top Taggers or The End of QCD?*, *JHEP* **05** (2017) 006, [1701.08784]. 3

[37] S. Macaluso and D. Shih, *Pulling Out All the Tops with Computer Vision and Deep Learning*, *JHEP* **10** (2018) 121, [1803.00107]. 3

[38] J. Li, T. Li and F.-Z. Xu, *Reconstructing boosted Higgs jets from event image segmentation*, 2008.13529.

[39] J. Li and H. Sun, *An Attention Based Neural Network for Jet Tagging*, 2009.00170.

[40] J. S. H. Lee, I. Park, I. J. Watson and S. Yang, *Quark-Gluon Jet Discrimination Using Convolutional Neural Networks*, *J. Korean Phys. Soc.* **74** (2019) 219–223, [2012.02531]. 3

[41] J. Collado, K. Bauer, E. Witkowski, T. Faucett, D. Whiteson and P. Baldi, *Learning to Isolate Muons*, 2021. 2

[42] Y.-L. Du, D. Pablos and K. Tywoniuk, *Deep learning jet modifications in heavy-ion collisions*, 2012.07797. 2, 4, 6

[43] 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]. 2, 5

[44] 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. 6

[45] 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.

[46] Y.-L. Chung, S.-C. Hsu and B. Nachman, *Disentangling Boosted Higgs Boson Production Modes with Machine Learning*, 2009.05930. 3

[47] Y.-L. Du, K. Zhou, J. Steinheimer, L.-G. Pang, A. Motornenko, H.-S. Zong et al.,

Identifying the nature of the QCD transition in relativistic collision of heavy nuclei with deep learning, Eur. Phys. J. C **80** (2020) 516, [`1910.11530`]. 2, 4

[48] 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`]. 2, 3

[49] E. Bols, J. Kieseler, M. Verzetti, M. Stoye and A. Stakia, *Jet Flavour Classification Using DeepJet*, `2008.10519`. 3

[50] K. Goto, T. Suehara, T. Yoshioka, M. Kurata, H. Nagahara, Y. Nakashima et al., *Development of a Vertex Finding Algorithm using Recurrent Neural Network*, 2021. 2, 4, 5

[51] G. Louppe, K. Cho, C. Becot and K. Cranmer, *QCD-Aware Recursive Neural Networks for Jet Physics*, `1702.00748`. 2, 3

[52] T. Cheng, *Recursive Neural Networks in Quark/Gluon Tagging*, `1711.02633`. 2, 3

[53] I. Henrion, K. Cranmer, J. Bruna, K. Cho, J. Brehmer, G. Louppe et al., *Neural Message Passing for Jet Physics*, 2017. 2

[54] X. Ju et al., *Graph Neural Networks for Particle Reconstruction in High Energy Physics detectors, 33rd Annual Conference on Neural Information Processing Systems* (3, 2020) , [`2003.11603`]. 4

[55] 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`]. 6

[56] E. A. Moreno, O. Cerri, J. M. Duarte, H. B. Newman, T. Q. Nguyen, A. Periwal et al., *JEDI-net: a jet identification algorithm based on interaction networks, Eur. Phys. J. C* **80** (2020) 58, [`1908.05318`]. 3

[57] 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`]. 3

[58] 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`]. 3

[59] 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`. 3

[60] M. Abdughani, D. Wang, L. Wu, J. M. Yang and J. Zhao, *Probing triple Higgs coupling with machine learning at the LHC*, `2005.11086`.

[61] E. Bernreuther, T. Finke, F. Kahlhoefer, M. Krämer and A. Mück, *Casting a graph net to catch dark showers*, 2006.08639. 3

[62] Y. Iiyama et al., *Distance-Weighted Graph Neural Networks on FPGAs for Real-Time Particle Reconstruction in High Energy Physics*, *Front. Big Data* **3** (2020) 598927, [2008.03601]. 5

[63] X. Ju and B. Nachman, *Supervised Jet Clustering with Graph Neural Networks for Lorentz Boosted Bosons*, *Phys. Rev. D* **102** (2020) 075014, [2008.06064]. 3

[64] N. Choma et al., *Track Seeding and Labelling with Embedded-space Graph Neural Networks*, 2007.00149. 4

[65] S. Alonso-Monsalve, D. Douqa, C. Jesus-Valls, T. Lux, S. Pina-Otey, F. Sanchez et al., *Graph neural network for 3D classification of ambiguities and optical crosstalk in scintillator-based neutrino detectors*, 2009.00688. 4

[66] Jun Guo and Jinmian Li and Tianjun Li, *The Boosted Higgs Jet Reconstruction via Graph Neural Network*, 2010.05464. 3

[67] A. Heintz et al., *Accelerated Charged Particle Tracking with Graph Neural Networks on FPGAs*, *34th Conference on Neural Information Processing Systems* (11, 2020) , [2012.01563]. 5

[68] Y. Verma and S. Jena, *Particle Track Reconstruction using Geometric Deep Learning*, 2012.08515. 4

[69] F. A. Dreyer and H. Qu, *Jet tagging in the Lund plane with graph networks*, 2012.08526. 3

[70] Z. Qian et al., *Vertex and Energy Reconstruction in JUNO with Machine Learning Methods*, 2101.04839. 4

[71] J. Pata, J. Duarte, J.-R. Vlimant, M. Pierini and M. Spiropulu, *MLPF: Efficient machine-learned particle-flow reconstruction using graph neural networks*, 2101.08578. 2

[72] P. T. Komiske, E. M. Metodiev and J. Thaler, *Energy Flow Networks: Deep Sets for Particle Jets*, *JHEP* **01** (2019) 121, [1810.05165]. 2

[73] H. Qu and L. Gouskos, *ParticleNet: Jet Tagging via Particle Clouds*, *Phys. Rev. D* **101** (2020) 056019, [1902.08570].

[74] V. Mikuni and F. Canelli, *ABCNet: An attention-based method for particle tagging*, *Eur. Phys. J. Plus* **135** (2020) 463, [2001.05311].

[75] J. Shlomi, S. Ganguly, E. Gross, K. Cranmer, Y. Lipman, H. Serviansky et al., *Secondary Vertex Finding in Jets with Neural Networks*, 2008.02831. 4

[76] M. J. Dolan and A. Ore, *Equivariant Energy Flow Networks for Jet Tagging*, 2012.00964.

[77] M. J. Fenton, A. Shmakov, T.-W. Ho, S.-C. Hsu, D. Whiteson and P. Baldi, *Permutationless Many-Jet Event Reconstruction with Symmetry Preserving Attention Networks*, 2010.09206.

[78] J. S. H. Lee, I. Park, I. J. Watson and S. Yang, *Zero-Permutation Jet-Parton Assignment using a Self-Attention Network*, 2012.03542. 2

[79] K. Datta, A. Larkoski and B. Nachman, *Automating the Construction of Jet Observables with Machine Learning*, 1902.07180. 2

[80] K. Datta and A. Larkoski, *How Much Information is in a Jet?*, *JHEP* **06** (2017) 073, [1704.08249].

[81] K. Datta and A. J. Larkoski, *Novel Jet Observables from Machine Learning*, *JHEP* **03** (2018) 086, [1710.01305].

[82] 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].

[83] A. Butter, G. Kasieczka, T. Plehn and M. Russell, *Deep-learned Top Tagging with a Lorentz Layer*, *SciPost Phys.* **5** (2018) 028, [1707.08966]. 2, 3

[84] CMS collaboration, A. M. Sirunyan et al., *Identification of heavy, energetic, hadronically decaying particles using machine-learning techniques*, *JINST* **15** (2020) P06005, [2004.08262]. 3

[85] 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]. 3

[86] K. Datta, A. Larkoski and B. Nachman, *Automating the Construction of Jet Observables with Machine Learning*, *Phys. Rev. D* **100** (2019) 095016, [1902.07180]. 3

[87] E. A. Moreno, T. Q. Nguyen, J.-R. Vlimant, O. Cerri, H. B. Newman, A. Periwal et al., *Interaction networks for the identification of boosted $H \to b\bar{b}$ decays*, *Phys. Rev. D* **102** (2020) 012010, [1909.12285].

[88] B. Tannenwald, C. Neu, A. Li, G. Buehlmann, A. Cuddeback, L. Hatfield et al., *Benchmarking Machine Learning Techniques with Di-Higgs Production at the LHC*, 2009.06754.

[89] M. Abbas, A. Khan, A. S. Qureshi and M. W. Khan, *Extracting Signals of Higgs Boson From Background Noise Using Deep Neural Networks*, 2010.08201. 3

[90] 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. 3

[91] Y.-T. Chien and R. Kunnawalkam Elayavalli, *Probing heavy ion collisions using quark and gluon jet substructure*, 1803.03589. 4

[92] G. Kasieczka, N. Kiefer, T. Plehn and J. M. Thompson, *Quark-Gluon Tagging: Machine Learning vs Detector*, *SciPost Phys.* **6** (2019) 069, [1812.09223].

[93] G. Kasieczka, S. Marzani, G. Soyez and G. Stagnitto, *Towards Machine Learning Analytics for Jet Substructure*, 2007.04319.

[94] J. S. H. Lee, S. M. Lee, Y. Lee, I. Park, I. J. Watson and S. Yang, *Quark Gluon Jet Discrimination with Weakly Supervised Learning*, *J. Korean Phys. Soc.* **75** (2019) 652–659, [2012.02540]. 3, 4

[95] S. Diefenbacher, H. Frost, G. Kasieczka, T. Plehn and J. M. Thompson, *CapsNets Continuing the Convolutional Quest*, *SciPost Phys.* **8** (2020) 023, [1906.11265]. 3, 9

[96] S. Bhattacharya, M. Guchait and A. H. Vijay, *Boosted Top Quark Tagging and Polarization Measurement using Machine Learning*, 2010.11778.

[97] S. H. Lim and M. M. Nojiri, *Morphology for Jet Classification*, 2010.13469.

[98] J. A. Aguilar-Saavedra, *Pulling the Higgs and Top needles from the jet stack with Feature Extended Supervised Tagging*, 2102.01667. 3

[99] Y. Nakai, D. Shih and S. Thomas, *Strange Jet Tagging*, 2003.09517. 3

[100] J. Erdmann, *A tagger for strange jets based on tracking information using long short-term memory*, *JINST* **15** (2020) P01021, [1907.07505].

[101] J. Erdmann, O. Nackenhorst and S. V. Zeißner, *Maximum performance of strange-jet tagging at hadron colliders*, 2011.10736. 3

[102] CMS collaboration, A. M. Sirunyan et al., *Identification of heavy-flavour jets with the CMS detector in pp collisions at 13 TeV*, 1712.07158. 3

[103] J. Bielcikoaá, R. K. Elayavalli, G. Ponimatkin, J. H. Putschke and J. Sivic, *Identifying Heavy-Flavor Jets Using Vectors of Locally Aggregated Descriptors*, 2005.01842. 3

[104] S. Bhattacharya, S. Nandi, S. K. Patra and S. Sahoo, *'Deep' Dive into $b \to c$ Anomalies: Standardized and Future-proof Model Selection Using Self-normalizing Neural Networks*, 2008.04316. 3

[105] 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]. 3

[106] C. Collaboration, *A deep neural network to search for new long-lived particles decaying to jets*, *Machine Learning: Science and Technology* (2020) , [1912.12238]. 6

[107] J. Alimena, Y. Iiyama and J. Kieseler, *Fast convolutional neural networks for identifying long-lived particles in a high-granularity calorimeter*, 2004.10744. 5

[108] S. Chang, T.-K. Chen and C.-W. Chiang, *Distinguishing W' Signals at Hadron Colliders Using Neural Networks*, 2007.14586.

[109] D. Cogollo, F. Freitas, C. S. Pires, Y. M. Oviedo-Torres and P. Vasconcelos, *Deep learnig analysis of the inverse seesaw in a 3-3-1 model at the LHC*, 2008.03409.

[110] M. Grossi, J. Novak, D. Rebuzzi and B. Kersevan, *Comparing Traditional and Deep-Learning Techniques of Kinematic Reconstruction for polarisation Discrimination in Vector Boson Scattering*, 2008.05316.

[111] V. S. Ngairangbam, A. Bhardwaj, P. Konar and A. K. Nayak, *Invisible Higgs search through Vector Boson Fusion: A deep learning approach*, 2008.05434.

[112] C. Englert, M. Fairbairn, M. Spannowsky, P. Stylianou and S. Varma, *Sensing Higgs cascade decays through memory*, 2008.08611.

[113] F. F. Freitas, J. a. Gonçalves, A. P. Morais and R. Pasechnik, *Phenomenology of vector-like leptons with Deep Learning at the Large Hadron Collider*, 2010.01307.

[114] C. K. Khosa, V. Sanz and M. Soughton, *WIMPs or else? Using Machine Learning to disentangle LHC signatures*, 1910.06058.

[115] F. F. Freitas, C. K. Khosa and V. Sanz, *Exploring the standard model EFT in VH production with machine learning*, Phys. Rev. D **100** (2019) 035040, [1902.05803]. 3

[116] L. De Oliveira, B. Nachman and M. Paganini, *Electromagnetic Showers Beyond Shower Shapes*, Nucl. Instrum. Meth. A **951** (2020) 162879, [1806.05667]. 3

[117] M. Paganini, L. de Oliveira and B. Nachman, *Survey of Machine Learning Techniques for High Energy Electromagnetic Shower Classification*, 2017.

[118] 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. 6, 7

[119] D. Belayneh et al., *Calorimetry with Deep Learning: Particle Simulation and Reconstruction for Collider Physics*, 1912.06794. 7

[120] J. Collado, J. N. Howard, T. Faucett, T. Tong, P. Baldi and D. Whiteson, *Learning to Identify Electrons*, 2011.01984. 3

[121] 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]. 4

[122] 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].

[123] 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].

[124] L. Hertel, L. Li, P. Baldi and J. Bian, *Convolutional Neural Networks for Electron Neutrino and Electron Shower Energy Reconstruction in the NOνA Detectors*, 2017.

[125] KM3NET collaboration, S. Aiello et al., *Event reconstruction for KM3NeT/ORCA using convolutional neural networks*, 2004.08254.

[126] C. Adams, K. Terao and T. Wongjirad, *PILArNet: Public Dataset for Particle Imaging Liquid Argon Detectors in High Energy Physics*, 2006.01993.

[127] 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.

[128] DEEPLEARNPHYSICS collaboration, D. H. Koh, P. C. de Soux, L. Domine, F. Drielsma, R. Itay, Q. Lin et al., *Scalable, Proposal-free Instance Segmentation Network for 3D Pixel Clustering and Particle Trajectory Reconstruction in Liquid Argon Time Projection Chambers*, 2007.03083.

[129] H. Yu et al., *Augmented Signal Processing in Liquid Argon Time Projection Chamber with Deep Neural Network*, 2007.12743.

[130] MICROBOONE collaboration, P. Abratenko et al., *A Convolutional Neural Network for Multiple Particle Identification in the MicroBooNE Liquid Argon Time Projection Chamber*, 2010.08653.

[131] B. Clerbaux, P.-A. Petitjean, Y. Xu and Y. Yang, *Study of using machine learning for level 1 trigger decision in JUNO experiment*, 2011.08847.

[132] J. Liu, J. Ott, J. Collado, B. Jargowsky, W. Wu, J. Bian et al., *Deep-Learning-Based Kinematic Reconstruction for DUNE*, 2012.06181.

[133] MICROBOONE collaboration, P. Abratenko et al., *Semantic Segmentation with a Sparse Convolutional Neural Network for Event Reconstruction in MicroBooNE*, 2012.08513.

[134] S. Y.-C. Chen, T.-C. Wei, C. Zhang, H. Yu and S. Yoo, *Quantum Convolutional Neural Networks for High Energy Physics Data Analysis*, 2012.12177. 5

[135] ICECUBE collaboration, R. Abbasi et al., *A Convolutional Neural Network based Cascade Reconstruction for the IceCube Neutrino Observatory*, 2021.

[136] F. Drielsma, K. Terao, L. Dominé and D. H. Koh, *Scalable, End-to-End, Deep-Learning-Based Data Reconstruction Chain for Particle Imaging Detectors*, in *34th Conference on Neural Information Processing Systems*, 2, 2021. 2102.01033. 4

[137] A. Ilyasov and A. Grobov, *Boosted decision trees approach to neck alpha events discrimination in DEAP-3600 experiment*, *Physica Scripta* (2020) . 4

[138] LUX collaboration, D. Akerib et al., *Improving sensitivity to low-mass dark matter in LUX using a novel electrode background mitigation technique*, 2011.09602.

[139] C. K. Khosa, L. Mars, J. Richards and V. Sanz, *Convolutional Neural Networks for Direct Detection of Dark Matter*, *J. Phys. G* **47** (2020) 095201, [1911.09210]. 4

[140] B. Ostdiek, A. Diaz Rivero and C. Dvorkin, *Detecting Subhalos in Strong Gravitational Lens Images with Image Segmentation*, 2009.06663. 4

[141] J. Brehmer, S. Mishra-Sharma, J. Hermans, G. Louppe and K. Cranmer, *Mining for Dark Matter Substructure: Inferring subhalo population properties from strong lenses with machine learning*, 1909.02005.

[142] Y.-L. S. Tsai, Y.-L. Chung, Q. Yuan and K. Cheung, *Inverting cosmic ray propagation by Convolutional Neural Networks*, 2011.11930.

[143] Pierre Auger collaboration, A. Aab et al., *Deep-Learning based Reconstruction of the Shower Maximum X_{max} using the Water-Cherenkov Detectors of the Pierre Auger Observatory*, 2101.02946.

[144] DarkMachines High Dimensional Sampling Group collaboration, C. Balázs et al., *A comparison of optimisation algorithms for high-dimensional particle and astrophysics applications*, 2101.04525. 5

[145] B. S. González, R. C. ao, M. Pimenta, B. Tomé and A. Guillén, *Tackling the muon identification in water Cherenkov detectors problem for the future Southern Wide-field Gamma-ray Observatory by means of Machine Learning*, 2021.

[146] R. Conceição, B. S. González, A. Guillén, M. Pimenta and B. Tomé, *Muon identification in a compact single-layered water Cherenkov detector and gamma/hadron discrimination using Machine Learning techniques*, 2101.10109.

[147] W.-C. Huang, J.-L. Kuo and Y.-L. S. Tsai, *A convolutional-neural-network estimator of CMB constraints on dark matter energy injection*, 2021. 4

[148] S. Farrell, P. Calafiura, M. Mudigonda, Prabhat, D. Anderson, J. Bendavid et al., *Particle Track Reconstruction with Deep Learning*, 2017. 4

[149] S. Farrell et al., *Novel deep learning methods for track reconstruction*, *4th International Workshop Connecting The Dots 2018* (10, 2018) , [1810.06111].

[150] S. Amrouche et al., *The Tracking Machine Learning challenge : Accuracy phase*, 1904.06778.

[151] S. Akar, T. J. Boettcher, S. Carl, H. F. Schreiner, M. D. Sokoloff, M. Stahl et al., *An

updated hybrid deep learning algorithm for identifying and locating primary vertices, 2007.01023.

[152] F. Siviero, R. Arcidiacono, N. Cartiglia, M. Costa, M. Ferrero, M. Mandurrino et al., *First application of machine learning algorithms to the position reconstruction in Resistive Silicon Detectors*, 2011.02410.

[153] P. J. Fox, S. Huang, J. Isaacson, X. Ju and B. Nachman, *Beyond 4D Tracking: Using Cluster Shapes for Track Seeding*, 2012.04533.

[154] S. Amrouche, M. Kiehn, T. Golling and A. Salzburger, *Hashing and metric learning for charged particle tracking*, *33rd Annual Conference on Neural Information Processing Systems* (1, 2021) , [2101.06428]. 4

[155] L.-G. Pang, K. Zhou, N. Su, H. Petersen, H. Stöcker and X.-N. Wang, *An equation-of-state-meter of quantum chromodynamics transition from deep learning*, *Nature Commun.* **9** (2018) 210, [1612.04262]. 4

[156] L. Tani, D. Rand, C. Veelken and M. Kadastik, *Evolutionary algorithms for hyperparameter optimization in machine learning for application in high energy physics*, 2011.04434. 4

[157] L. M. Dery, B. Nachman, F. Rubbo and A. Schwartzman, *Weakly Supervised Classification in High Energy Physics*, *JHEP* **05** (2017) 145, [1702.00414]. 4

[158] 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].

[159] 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]. 8

[160] J. H. Collins, K. Howe and B. Nachman, *Extending the search for new resonances with machine learning*, *Phys. Rev.* **D99** (2019) 014038, [1902.02634]. 8

[161] M. Borisyak and N. Kazeev, *Machine Learning on data with sPlot background subtraction*, 1905.11719.

[162] T. Cohen, M. Freytsis and B. Ostdiek, *(Machine) Learning to Do More with Less*, 1706.09451.

[163] P. T. Komiske, E. M. Metodiev and J. Thaler, *An operational definition of quark and gluon jets*, *JHEP* **11** (2018) 059, [1809.01140].

[164] E. M. Metodiev and J. Thaler, *Jet Topics: Disentangling Quarks and Gluons at Colliders*, *Phys. Rev. Lett.* **120** (2018) 241602, [1802.00008].

[165] ATLAS Collaboration, *Dijet resonance search with weak supervision using 13 TeV pp collisions in the ATLAS detector*, 2005.02983. 8, 9

[166] O. Amram and C. M. Suarez, *Tag N' Train: A Technique to Train Improved Classifiers on Unlabeled Data*, 2002.12376. 8

[167] J. Brewer, J. Thaler and A. P. Turner, *Data-driven quark and gluon jet modification in heavy-ion collisions*, 2008.08596.

[168] S.-e. Dahbi, J. Choma, B. Mellado, G. Mokgatitswane, X. Ruan, T. Celik et al., *Machine learning approach for the search of resonances with topological features at the Large Hadron Collider*, 2011.09863. 4

[169] L. Mackey, B. Nachman, A. Schwartzman and C. Stansbury, *Fuzzy Jets*, *JHEP* **06** (2016) 010, [1509.02216]. 4

[170] P. T. Komiske, E. M. Metodiev and J. Thaler, *Metric Space of Collider Events*, *Phys. Rev. Lett.* **123** (2019) 041801, [1902.02346].

[171] B. M. Dillon, D. A. Faroughy, J. F. Kamenik and M. Szewc, *Learning the latent structure of collider events*, 2005.12319. 8

[172] B. M. Dillon, D. A. Faroughy and J. F. Kamenik, *Uncovering latent jet substructure*, *Phys. Rev.* **D100** (2019) 056002, [1904.04200]. 8

[173] T. Cai, J. Cheng, K. Craig and N. Craig, *Linearized Optimal Transport for Collider Events*, 2008.08604.

[174] J. N. Howard, S. Mandt, D. Whiteson and Y. Yang, *Foundations of a Fast, Data-Driven, Machine-Learned Simulator*, 2101.08944. 4, 7, 8

[175] S. Carrazza and F. A. Dreyer, *Jet grooming through reinforcement learning*, *Phys. Rev. D* **100** (2019) 014014, [1903.09644]. 5, 6

[176] J. Brehmer, S. Macaluso, D. Pappadopulo and K. Cranmer, *Hierarchical clustering in particle physics through reinforcement learning*, *34th Conference on Neural Information Processing Systems* (11, 2020) , [2011.08191].

[177] J. S. John et al., *Real-time Artificial Intelligence for Accelerator Control: A Study at the Fermilab Booster*, 2011.07371. 5

[178] A. Mott, J. Job, J. R. Vlimant, D. Lidar and M. Spiropulu, *Solving a Higgs optimization problem with quantum annealing for machine learning*, *Nature* **550** (2017) 375–379. 5

[179] A. Zlokapa, A. Mott, J. Job, J.-R. Vlimant, D. Lidar and M. Spiropulu, *Quantum adiabatic machine learning with zooming*, 1908.04480.

[180] A. Blance and M. Spannowsky, *Quantum Machine Learning for Particle Physics using a Variational Quantum Classifier*, 2010.07335.

[181] K. Terashi, M. Kaneda, T. Kishimoto, M. Saito, R. Sawada and J. Tanaka, *Event Classification with Quantum Machine Learning in High-Energy Physics*, 2002.09935.

[182] S. L. Wu et al., *Application of Quantum Machine Learning using the Quantum Variational Classifier Method to High Energy Physics Analysis at the LHC on IBM Quantum Computer Simulator and Hardware with 10 qubits*, `2012.11560`.

[183] S. Y.-C. Chen, T.-C. Wei, C. Zhang, H. Yu and S. Yoo, *Hybrid Quantum-Classical Graph Convolutional Network*, `2101.06189`. 5

[184] T. Faucett, J. Thaler and D. Whiteson, *Mapping Machine-Learned Physics into a Human-Readable Space*, `2010.11998`. 5

[185] J. Y. Araz and M. Spannowsky, *Combine and Conquer: Event Reconstruction with Bayesian Ensemble Neural Networks*, `2102.01078`. 5, 9

[186] 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`. 5

[187] 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`].

[188] 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.

[189] D. Bourgeois, C. Fitzpatrick and S. Stahl, *Using holistic event information in the trigger*, `1808.00711`. 5

[190] J. Duarte et al., *Fast inference of deep neural networks in FPGAs for particle physics*, *JINST* **13** (2018) P07027, [`1804.06913`]. 5

[191] J. Ngadiuba et al., *Compressing deep neural networks on FPGAs to binary and ternary precision with HLS4ML, Mach. Learn.: Sci. Tech.* **2** (2020) 015001, [`2003.06308`].

[192] S. Summers et al., *Fast inference of Boosted Decision Trees in FPGAs for particle physics*, *JINST* **15** (2020) P05026, [`2002.02534`].

[193] J. Krupa et al., *GPU coprocessors as a service for deep learning inference in high energy physics*, `2007.10359`.

[194] L. R. M. Mohan, A. Marshall, S. Maddrell-Mander, D. O'Hanlon, K. Petridis, J. Rademacker et al., *Studying the potential of Graphcore IPUs for applications in Particle Physics*, `2008.09210`.

[195] S. Carrazza, J. M. Cruz-Martinez and M. Rossi, *PDFFlow: parton distribution functions on GPU*, `2009.06635`.

[196] D. S. Rankin et al., *FPGAs-as-a-Service Toolkit (FaaST), 2020 IEEE/ACM International Workshop on Heterogeneous High-performance Reconfigurable Computing (H2RC)* (10, 2020) 38, [`2010.08556`].

[197] M. Rossi, S. Carrazza and J. M. Cruz-Martinez, *PDFFlow: hardware accelerating parton density access*, 2012.08221. 6

[198] T. Aarrestad et al., *Fast convolutional neural networks on FPGAs with hls4ml*, 2101.05108. 5

[199] V. Kuznetsov, L. Giommi and D. Bonacorsi, *MLaaS4HEP: Machine Learning as a Service for HEP*, 2007.14781. 5

[200] P. T. Komiske, E. M. Metodiev, B. Nachman and M. D. Schwartz, *Pileup Mitigation with Machine Learning (PUMML)*, JHEP **12** (2017) 051, [1707.08600]. 6

[201] S. Cheong, A. Cukierman, B. Nachman, M. Safdari and A. Schwartzman, *Parametrizing the Detector Response with Neural Networks*, JINST **15** (2020) P01030, [1910.03773]. 6

[202] ATLAS Collaboration collaboration, *Simultaneous Jet Energy and Mass Calibrations with Neural Networks*, Tech. Rep. ATL-PHYS-PUB-2020-001, CERN, Geneva, Jan, 2020.

[203] ATLAS Collaboration collaboration, *Generalized Numerical Inversion: A Neural Network Approach to Jet Calibration*, Tech. Rep. ATL-PHYS-PUB-2018-013, CERN, Geneva, Jul, 2018.

[204] G. Kasieczka, M. Luchmann, F. Otterpohl and T. Plehn, *Per-Object Systematics using Deep-Learned Calibration*, 2003.11099.

[205] CMS collaboration, A. M. Sirunyan et al., *A deep neural network for simultaneous estimation of b jet energy and resolution*, 1912.06046.

[206] P. Baldi, L. Blecher, A. Butter, J. Collado, J. N. Howard, F. Keilbach et al., *How to GAN Higher Jet Resolution*, 2012.11944. 6

[207] 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. 6

[208] 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. 8

[209] B. Kronheim, M. Kuchera, H. Prosper and A. Karbo, *Bayesian Neural Networks for Fast SUSY Predictions*, 2007.04506. 6

[210] F. Bishara and M. Montull, *(Machine) Learning Amplitudes for Faster Event Generation*, 1912.11055. 6

[211] A. Buckley, A. Kvellestad, A. Raklev, P. Scott, J. V. Sparre, J. V. d. Abeele et al., *Xsec: the cross-section evaluation code*, 2006.16273. 8

[212] F. Bury and C. Delaere, *Matrix Element Regression with Deep Neural Networks – breaking the CPU barrier*, 2008.10949. 6

[213] Y.-K. Lei, C. Liu and Z. Chen, *Numerical analysis of neutrino physics within a high scale supersymmetry model via machine learning*, 2006.01495. 6

[214] S. Chen, A. Glioti, G. Panico and A. Wulzer, *Parametrized classifiers for optimal EFT sensitivity*, 2007.10356.

[215] M. Lazzarin, S. Alioli and S. Carrazza, *MCNNTUNES: tuning Shower Monte Carlo generators with machine learning*, 2010.02213. 6

[216] L. Del Debbio, T. Giani, J. Karpie, K. Orginos, A. Radyushkin and S. Zafeiropoulos, *Neural-network analysis of Parton Distribution Functions from Ioffe-time pseudodistributions*, 2010.03996. 6

[217] J. Grigsby, B. Kriesten, J. Hoskins, S. Liuti, P. Alonzi and M. Burkardt, *Deep Learning Analysis of Deeply Virtual Exclusive Photoproduction*, 2012.04801. 6

[218] 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. 6, 7

[219] M. Favoni, A. Ipp, D. I. Müller and D. Schuh, *Lattice gauge equivariant convolutional neural networks*, 2012.12901. 6

[220] G. Louppe, M. Kagan and K. Cranmer, *Learning to Pivot with Adversarial Networks*, 1611.01046. 6, 9

[221] 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].

[222] I. Moult, B. Nachman and D. Neill, *Convolved Substructure: Analytically Decorrelating Jet Substructure Observables*, *JHEP* **05** (2018) 002, [1710.06859].

[223] J. Stevens and M. Williams, *uBoost: A boosting method for producing uniform selection efficiencies from multivariate classifiers*, *JINST* **8** (2013) P12013, [1305.7248].

[224] C. Shimmin, P. Sadowski, P. Baldi, E. Weik, D. Whiteson, E. Goul et al., *Decorrelated Jet Substructure Tagging using Adversarial Neural Networks*, 1703.03507.

[225] L. Bradshaw, R. K. Mishra, A. Mitridate and B. Ostdiek, *Mass Agnostic Jet Taggers*, 1908.08959.

[226] ATLAS collaboration, *Performance of mass-decorrelated jet substructure observables for hadronic two-body decay tagging in ATLAS*, *ATL-PHYS-PUB-2018-014* (2018) .

[227] G. Kasieczka and D. Shih, *DisCo Fever: Robust Networks Through Distance Correlation*, 2001.05310.

[228] 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].

[229] C. Englert, P. Galler, P. Harris and M. Spannowsky, *Machine Learning Uncertainties with Adversarial Neural Networks*, *Eur. Phys. J.* **C79** (2019) 4, [1807.08763]. 9

[230] S. Wunsch, S. Jórger, R. Wolf and G. Quast, *Reducing the dependence of the neural network function to systematic uncertainties in the input space*, 1907.11674.

[231] A. Rogozhnikov, A. Bukva, V. V. Gligorov, A. Ustyuzhanin and M. Williams, *New approaches for boosting to uniformity*, *JINST* **10** (2015) T03002, [1410.4140].

[232] J. M. Clavijo, P. Glaysher and J. M. Katzy, *Adversarial domain adaptation to reduce sample bias of a high energy physics classifier*, 2005.00568.

[233] G. Kasieczka, B. Nachman, M. D. Schwartz and D. Shih, *ABCDisCo: Automating the ABCD Method with Machine Learning*, 2007.14400.

[234] O. Kitouni, B. Nachman, C. Weisser and M. Williams, *Enhancing searches for resonances with machine learning and moment decomposition*, 2010.09745. 6

[235] L. de Oliveira, M. Paganini and B. Nachman, *Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis*, 1701.05927. 7

[236] 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].

[237] 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].

[238] S. Alonso-Monsalve and L. H. Whitehead, *Image-based model parameter optimization using Model-Assisted Generative Adversarial Networks*, 1812.00879.

[239] A. Butter, T. Plehn and R. Winterhalder, *How to GAN Event Subtraction*, 1912.08824.

[240] 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*, *ACAT 2019* (2019) , [1912.02748].

[241] M. Bellagente, A. Butter, G. Kasieczka, T. Plehn and R. Winterhalder, *How to GAN away Detector Effects*, 1912.00477. 8

[242] 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.

[243] SHiP collaboration, C. Ahdida et al., *Fast simulation of muons produced at the SHiP experiment using Generative Adversarial Networks*, 1909.04451.

[244] S. Carrazza and F. A. Dreyer, *Lund jet images from generative and cycle-consistent adversarial networks*, *Eur. Phys. J.* **C79** (2019) 979, [1909.01359].

[245] A. Butter, T. Plehn and R. Winterhalder, *How to GAN LHC Events*, *SciPost Phys.* **7** (2019) 075, [1907.03764].

[246] 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].

[247] R. Di Sipio, M. Faucci 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.

[248] B. Hashemi, N. Amin, K. Datta, D. Olivito and M. Pierini, *LHC analysis-specific datasets with Generative Adversarial Networks*, 1901.05282.

[249] V. Chekalina, E. Orlova, F. Ratnikov, D. Ulyanov, A. Ustyuzhanin and E. Zakharov, *Generative Models for Fast Calorimeter Simulation.LHCb case*, *CHEP 2018* (2018) , [1812.01319].

[250] ATLAS collaboration, *Deep generative models for fast shower simulation in ATLAS*, *ATL-SOFT-PUB-2018-001* (Jul, 2018) . 7

[251] 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].

[252] 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.

[253] 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.

[254] K. Datta, D. Kar and D. Roy, *Unfolding with Generative Adversarial Networks*, 1806.00433. 8

[255] 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].

[256] 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].

[257] 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.

[258] D. Derkach, N. Kazeev, F. Ratnikov, A. Ustyuzhanin and A. Volokhova, *RICH 2018*, 1903.11788.

[259] H. Erbin and S. Krippendorf, *GANs for generating EFT models*, 1809.02612.

[260] 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].

[261] J. M. Urban and J. M. Pawlowski, *Reducing Autocorrelation Times in Lattice Simulations with Generative Adversarial Networks*, 1811.03533.

[262] L. de Oliveira, M. Paganini and B. Nachman, *Tips and Tricks for Training GANs with Physics Constraints*, 2017.

[263] 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].

[264] 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.

[265] 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.

[266] Y. Alanazi et al., *AI-based Monte Carlo event generator for electron-proton scattering*, 2008.03151.

[267] S. Diefenbacher, E. Eren, G. Kasieczka, A. Korol, B. Nachman and D. Shih, *DCTRGAN: Improving the Precision of Generative Models with Reweighting*, *Journal of Instrumentation* **15** (2020) P11004, [2009.03796]. 8

[268] A. Butter, S. Diefenbacher, G. Kasieczka, B. Nachman and T. Plehn, *GANplifying Event Samples*, 2008.06545.

[269] R. Kansal, J. Duarte, B. Orzari, T. Tomei, M. Pierini, M. Touranakou et al., *Graph Generative Adversarial Networks for Sparse Data Generation in High Energy Physics*, *34th Conference on Neural Information Processing Systems* (11, 2020) , [2012.00173].

[270] A. Maevskiy, F. Ratnikov, A. Zinchenko and V. Riabov, *Simulating the Time Projection Chamber responses at the MPD detector using Generative Adversarial Networks*, 2012.04595.

[271] Y. S. Lai, D. Neill, M. Płoskoń and F. Ringer, *Explainable machine learning of the underlying physics of high-energy particle collisions*, 2012.06582. 7

[272] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair et al., *Generative Adversarial Networks*, 1406.2661. 7

[273] J. W. Monk, *Deep Learning as a Parton Shower*, 1807.03685. 7

[274] T. Cheng, J.-F. Arguin, J. Leissner-Martin, J. Pilette and T. Golling, *Variational Autoencoders for Anomalous Jet Tagging*, 2007.01850. 8

[275] K. Dohi, *Variational Autoencoders for Jet Simulation*, 2009.04842. 7

[276] 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]. 7

[277] J. Brehmer and K. Cranmer, *Flows for simultaneous manifold learning and density estimation*, 2003.13913.

[278] E. Bothmann, T. Janßen, M. Knobbe, T. Schmale and S. Schumann, *Exploring phase space with Neural Importance Sampling*, 2001.05478. 8

[279] C. Gao, S. Höche, J. Isaacson, C. Krause and H. Schulz, *Event Generation with Normalizing Flows*, Phys. Rev. D **101** (2020) 076002, [2001.10028].

[280] C. Gao, J. Isaacson and C. Krause, *i-flow: High-Dimensional Integration and Sampling with Normalizing Flows*, 2001.05486. 8

[281] B. Nachman and D. Shih, *Anomaly Detection with Density Estimation*, Phys. Rev. D **101** (2020) 075042, [2001.04990]. 8

[282] S. Choi, J. Lim and H. Oh, *Data-driven Estimation of Background Distribution through Neural Autoregressive Flows*, 2008.03636.

[283] Y. Lu, J. Collado, D. Whiteson and P. Baldi, *SARM: Sparse Autoregressive Model for Scalable Generation of Sparse Images in Particle Physics*, 2009.14017.

[284] S. Bieringer, A. Butter, T. Heimel, S. Höche, U. Köthe, T. Plehn et al., *Measuring QCD Splittings with Invertible Networks*, 2012.09873. 7, 8

[285] D. Rezende and S. Mohamed, *Variational inference with normalizing flows*, Proceedings of the 32nd International Conference on Machine Learning **37** (07–09 Jul, 2015) 1530–1538. 7

[286] A. Andreassen, I. Feige, C. Frye and M. D. Schwartz, *JUNIPR: a Framework for Unsupervised Machine Learning in Particle Physics*, 1804.09720. 7

[287] 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].

[288] M. Jercic and N. Poljak, *Exploring the Possibility of a Recovery of Physics Process Properties from a Neural Network Model*, 2007.13110. 7

[289] C. Chen, O. Cerri, T. Q. Nguyen, J.-R. Vlimant and M. Pierini, *Data Augmentation at the LHC through Analysis-specific Fast Simulation with Deep Learning*, 2010.01835. 7

[290] J. Bendavid, *Efficient Monte Carlo Integration Using Boosted Decision Trees and Generative Deep Neural Networks*, 1707.00028. 8

[291] M. D. Klimek and M. Perelstein, *Neural Network-Based Approach to Phase Space Integration*, 1810.11509.

[292] S. Carrazza and J. M. Cruz-Martinez, *VegasFlow: accelerating Monte Carlo simulation across multiple hardware platforms*, 2002.12921.

[293] B. Nachman and J. Thaler, *A Neural Resampler for Monte Carlo Reweighting with Preserved Uncertainties*, 2007.11586.

[294] I.-K. Chen, M. D. Klimek and M. Perelstein, *Improved Neural Network Monte Carlo Simulation*, 2009.07819.

[295] R. Verheyen and B. Stienen, *Phase Space Sampling and Inference from Weighted Events with Autoregressive Flows*, 2011.13445.

[296] M. Backes, A. Butter, T. Plehn and R. Winterhalder, *How to GAN Event Unweighting*, 2012.07873. 8

[297] M. Frate, K. Cranmer, S. Kalia, A. Vandenberg-Rodes and D. Whiteson, *Modeling Smooth Backgrounds and Generic Localized Signals with Gaussian Processes*, 1709.05681. 8

[298] R. T. D'Agnolo and A. Wulzer, *Learning New Physics from a Machine*, *Phys. Rev.* **D99** (2019) 015014, [1806.02350]. 8

[299] R. T. D'Agnolo, G. Grosso, M. Pierini, A. Wulzer and M. Zanetti, *Learning Multivariate New Physics*, 1912.12155.

[300] M. Farina, Y. Nakai and D. Shih, *Searching for New Physics with Deep Autoencoders*, 1808.08992.

[301] T. Heimel, G. Kasieczka, T. Plehn and J. M. Thompson, *QCD or What?*, *SciPost Phys.* **6** (2019) 030, [1808.08979].

[302] T. S. Roy and A. H. Vijay, *A robust anomaly finder based on autoencoder*, 1903.02032.

[303] 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`].

[304] A. Blance, M. Spannowsky and P. Waite, *Adversarially-trained autoencoders for robust unsupervised new physics searches*, *JHEP* **10** (2019) 047, [`1905.10384`].

[305] J. Hajer, Y.-Y. Li, T. Liu and H. Wang, *Novelty Detection Meets Collider Physics*, `1807.10261`.

[306] A. De Simone and T. Jacques, *Guiding New Physics Searches with Unsupervised Learning*, *Eur. Phys. J.* **C79** (2019) 289, [`1807.06038`].

[307] A. Mullin, H. Pacey, M. Parker, M. White and S. Williams, *Does SUSY have friends? A new approach for LHC event analysis*, `1912.10625`.

[308] G. M. Alessandro Casa, *Nonparametric semisupervised classification for signal detection in high energy physics*, `1809.02977`.

[309] A. Andreassen, B. Nachman and D. Shih, *Simulation Assisted Likelihood-free Anomaly Detection*, *Phys. Rev. D* **101** (2020) 095004, [`2001.05001`]. 8

[310] J. A. Aguilar-Saavedra, J. H. Collins and R. K. Mishra, *A generic anti-QCD jet tagger*, *JHEP* **11** (2017) 163, [`1709.01087`].

[311] 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`].

[312] 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`. 8

[313] 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`.

[314] M. C. Romao, N. Castro and R. Pedro, *Finding New Physics without learning about it: Anomaly Detection as a tool for Searches at Colliders*, `2006.05432`.

[315] C. K. Khosa and V. Sanz, *Anomaly Awareness*, `2007.14462`.

[316] P. Thaprasop, K. Zhou, J. Steinheimer and C. Herold, *Unsupervised Outlier Detection in Heavy-Ion Collisions*, `2007.15830`.

[317] S. Alexander, S. Gleyzer, H. Parul, P. Reddy, M. W. Toomey, E. Usai et al., *Decoding Dark Matter Substructure without Supervision*, `2008.12731`.

[318] J. A. Aguilar-Saavedra, F. R. Joaquim and J. F. Seabra, *Mass Unspecific Supervised Tagging (MUST) for boosted jets*, `2008.12792`.

[319] K. Benkendorfer, L. L. Pottier and B. Nachman, *Simulation-Assisted Decorrelation for Resonant Anomaly Detection*, 2009.02205.

[320] Adrian Alan Pol and Victor Berger and Gianluca Cerminara and Cecile Germain and Maurizio Pierini, *Anomaly Detection With Conditional Variational Autoencoders*, 2010.05531.

[321] V. Mikuni and F. Canelli, *Unsupervised clustering for collider physics*, 2010.07106.

[322] M. van Beekveld, S. Caron, L. Hendriks, P. Jackson, A. Leinweber, S. Otten et al., *Combining outlier analysis algorithms to identify new physics at the LHC*, 2010.07940.

[323] S. E. Park, D. Rankin, S.-M. Udrescu, M. Yunus and P. Harris, *Quasi Anomalous Knowledge: Searching for new physics with embedded knowledge*, 2011.03550.

[324] D. A. Faroughy, *Uncovering hidden patterns in collider events with Bayesian probabilistic models*, 2012.08579.

[325] G. Stein, U. Seljak and B. Dai, *Unsupervised in-distribution anomaly detection of new physics through conditional density estimation*, 2012.11638.

[326] G. Kasieczka et al., *The LHC Olympics 2020: A Community Challenge for Anomaly Detection in High Energy Physics*, 2101.08320. 8

[327] A. Andreassen and B. Nachman, *Neural Networks for Full Phase-space Reweighting and Parameter Tuning, Phys. Rev. D* **101** (2020) 091901, [1907.08209]. 8

[328] M. Stoye, J. Brehmer, G. Louppe, J. Pavez and K. Cranmer, *Likelihood-free inference with an improved cross-entropy estimator*, 1808.00973.

[329] J. Hollingsworth and D. Whiteson, *Resonance Searches with Machine Learned Likelihood Ratios*, 2002.04699. 8

[330] J. Brehmer, K. Cranmer, G. Louppe and J. Pavez, *Constraining Effective Field Theories with Machine Learning*, 1805.00013.

[331] J. Brehmer, K. Cranmer, G. Louppe and J. Pavez, *A Guide to Constraining Effective Field Theories with Machine Learning*, 1805.00020.

[332] 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].

[333] 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]. 8

[334] A. Andreassen, S.-C. Hsu, B. Nachman, N. Suaysom and A. Suresh, *Parameter Estimation using Neural Networks in the Presence of Detector Effects, Phys. Rev. D* **103** (2021) 036001, [2010.03569].

[335] A. Coogan, K. Karchev and C. Weniger, *Targeted Likelihood-Free Inference of Dark Matter Substructure in Strongly-Lensed Galaxies*, *34th Conference on Neural Information Processing Systems* (10, 2020) , [2010.07032].

[336] F. Flesher, K. Fraser, C. Hutchison, B. Ostdiek and M. D. Schwartz, *Parameter Inference from Event Ensembles and the Top-Quark Mass*, 2011.04666. 8

[337] 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]. 8

[338] N. D. Gagunashvili, *Machine learning approach to inverse problem and unfolding procedure*, 1004.2006.

[339] A. Glazov, *Machine learning as an instrument for data unfolding*, 1712.01814.

[340] D. Martschei, M. Feindt, S. Honc and J. Wagner-Kuhr, *Advanced event reweighting using multivariate analysis*, *J. Phys. Conf. Ser.* **368** (2012) 012028.

[341] L. Lindemann and G. Zech, *Unfolding by weighting Monte Carlo events*, *Nucl. Instrum. Meth. A* **354** (1995) 516–521.

[342] G. Zech and B. Aslan, *Binning-Free Unfolding Based on Monte Carlo Migration*, *PHYSTAT* (2003) .

[343] M. Bellagente, A. Butter, G. Kasieczka, T. Plehn, A. Rousselot and R. Winterhalder, *Invertible Networks or Partons to Detector and Back Again*, 2006.06685.

[344] M. Vandegar, M. Kagan, A. Wehenkel and G. Louppe, *Neural Empirical Bayes: Source Distribution Estimation and its Applications to Simulation-Based Inference*, 2011.05836. 8

[345] 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]. 8

[346] S. Chang, T. Cohen and B. Ostdiek, *What is the Machine Learning?*, *Phys. Rev.* **D97** (2018) 056009, [1709.10106]. 9

[347] G. Agarwal, L. Hay, I. Iashvili, B. Mannix, C. McLean, M. Morris et al., *Explainable AI for ML jet taggers using expert variables and layerwise relevance propagation*, 2011.13466. 9

[348] B. Nachman, *A guide for deploying Deep Learning in LHC searches: How to achieve optimality and account for uncertainty*, 1909.03081. 9

[349] B. Nachman and C. Shimmin, *AI Safety for High Energy Physics*, 1910.08606. 9

[350] V. Estrade, C. Germain, I. Guyon and D. Rousseau, *Adversarial learning to eliminate systematic errors: a case study in High Energy Physics*, 2017. 9

[351] S. Caron, T. Heskes, S. Otten and B. Stienen, *Constraining the Parameters of High-Dimensional Models with Active Learning*, *Eur. Phys. J.* **C79** (2019) 944, [1905.08628]. 9

[352] 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].

[353] P. De Castro and T. Dorigo, *INFERNO: Inference-Aware Neural Optimisation*, *Comput. Phys. Commun.* **244** (2019) 170–179, [1806.04743].

[354] 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. 9

[355] ATLAS collaboration, G. Aad et al., *Search for non-resonant Higgs boson pair production in the $bb\ell\nu\ell\nu$ final state with the ATLAS detector in pp collisions at $\sqrt{s} = 13$ TeV*, *Phys. Lett. B* **801** (2020) 135145, [1908.06765]. 9

[356] 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.

[357] CMS collaboration, A. M. Sirunyan et al., *Inclusive search for highly boosted Higgs bosons decaying to bottom quark-antiquark pairs in proton-proton collisions at $\sqrt{s} = 13$ TeV*, *JHEP* **12** (2020) 085, [2006.13251]. 9