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.

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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 [12–21]
    - Event images [16, 22, 23]
    - Sequences [24]
    - Trees [25, 26]
    - Graphs [27–33]
    - Sets (point clouds) [34, 35]
    - Physics-inspired basis [36–40]
  - Targets
    - W/Z tagging [14, 18, 25, 41, 42]
    - $H \to b\bar{b}$ [16, 32, 41, 43, 44]
    - quarks and gluons [15, 19, 26, 30, 45–47]
    - top quark tagging [6, 20, 21, 33, 40, 45, 48]
    - strange jets [49]
    - b-tagging [24, 50, 51]
    - BSM particles [32, 43, 52–54]
    - Particle identification [31, 55–58]

    * Neutrino Detectors [59–63]
    * Tracking [28, 64–66]
    * Heavy ions [46, 67]
  - Learning strategies
    * Weak supervision [17, 68–76]
    * Unsupervised [77, 78]
  - Fast inference
    * Software [54, 79–82]
    * Hardware/firmware [83–85]

- Regression.
  - Pileup [22, 29, 86, 87]
  - Calibration [57, 88–92]
  - Recasting [93, 94]
  - Matrix elements [95]
- Decorrelation methods [53, 96–108]
- Generative models / density estimation.
  - GANs [109]: [57, 58, 110–138]
  - Autoencoders [124, 139]
  - Physics-inspired [140, 141]
  - Normalizing flows [142]: [143–148]
  - Phase space generation [146–151]
  - Gaussian processes [94, 152]
- Anomaly detection [70, 71, 76, 153–168]
- Simulation-based ('likelihood-free') Inference.
  - Overview [169]
  - Parameter estimation [11, 170–176]
  - Unfolding [115, 128, 177–182]
  - Domain adaptation [11, 170, 183]

  - BSM [165, 172–176]

- Uncertainty Quantification.

  - Interpretability [14, 48, 184]
  - Estimation [18, 185, 186]
  - Mitigation [96, 105, 187]
  - Uncertainty-aware inference [188–191]

- 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 [76, 192, 193].

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