Any Idea How to Use Generative Networks?

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Working: ML classification

Neural networks to classify low-level detector output

- subjet physics taggers with CNNs etc
- uncertainties with Bayesian networks
- event classification and visualization with capsules
- unsupervised learning on background only

⇒ Why should only experiment benefit??

SciPost Physics — Submission

The Machine Learning Landscape of Top Taggers

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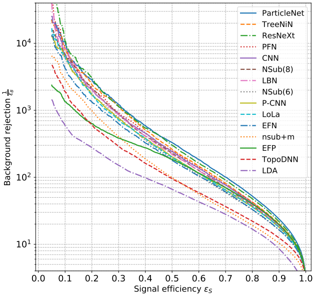
Abstract

Based on the established task of identifying boosted, hadronically decaying top quarks, we compare a wide range of modern machine learning approaches. We find that they are extremely powerful and great fun.



Theory: generative networks

Neural networks generating data [Butter, TP, Winterhalder: 1907.03764]

– learn pattern and transform noise into objects with same pattern

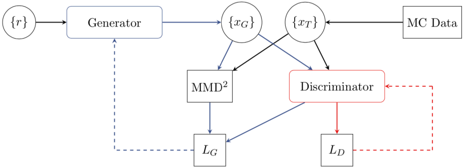
fast detector simulation [Paganini..., Musella..., Erdmann...]

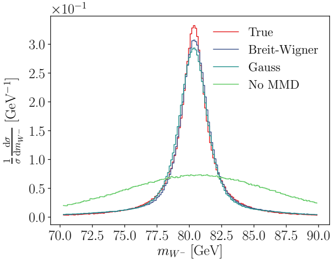
fast parton shower [de Oliveira..., Bothmann..., Monk, Carazza...]

– generate 4-vectors [Bendavit, Klimek..., Otten..., Hashemi..., Di Sipio...]

– challenge: resolution via kernels [MMD: maximum mean discrepancy]

phase space limits, cuts, intermediate Breit-Wigners [Higgs a problem: $\Gamma_H \ll m_H$]





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– application to $t\bar{t} \to 6$ jets
  new unweigted events from any sample
  Works, so what's next?