From Higgless models to Transformers:

Breaking the cut-offs in Physics and Machine Learning

Riccardo^3 Torre

INFN - Sezione di Genova

SNS - 09 November 2024

About some future directions in fundamental physics

a speculative talk in honour of Riccardo Barbieri

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*Many of the analogies I will introduce are speculative, even though there exist ongoing research aiming to make them formal

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arXiv:0911.1942v3 [hep-ph] 31 Mar 2010

Composite Vectors at the Large Hadron Collider

R. Barbieri[a,b], A.E. Cárcamo Hernández[a,b], G. Corcella[a,b,c],
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Abstract

An unspecified strong dynamics may give rise to composite vectors sufficiently light that their interactions, among themselves or with the electroweak gauge bosons, be approximately described by an effective Lagrangian invariant under $SU(2)_L \times SU(2)_R / SU(2)_{L+R}$. We study the production at the LHC of two such states by vector boson fusion or by the Drell–Yan process in this general framework and we compare it with the case of gauge vectors from a $SU(2)_L \times SU(2)_R \times SU(2)^N$ gauge model spontaneously broken to the diagonal $SU(2)$ subgroup by a generic σ-model. Special attention is payed to the asymptotic behaviour of the different amplitudes in both cases. The expected rates of multi-lepton events from the decay of the composite vectors are also given. A thorough phenomenological analysis and the evaluation of the backgrounds to such signals, aiming at assessing the visibility of composite-vector pairs at the LHC, is instead deferred to future work.

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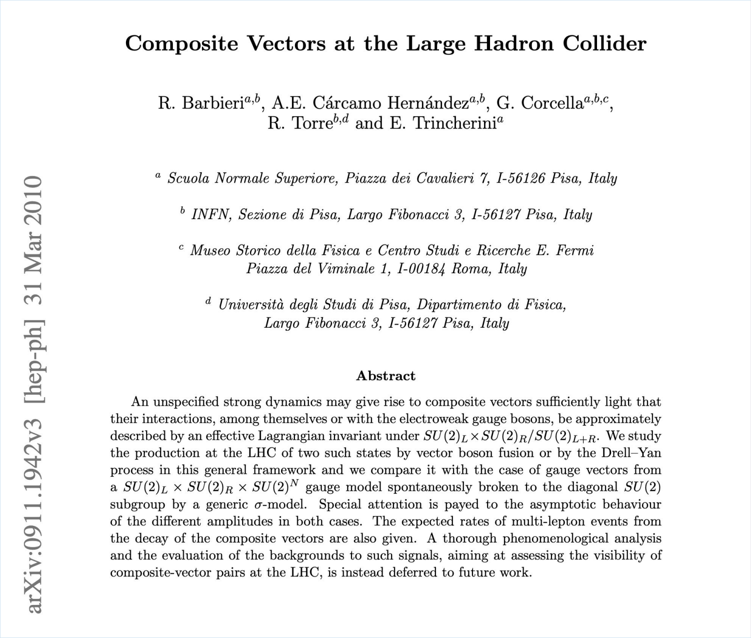

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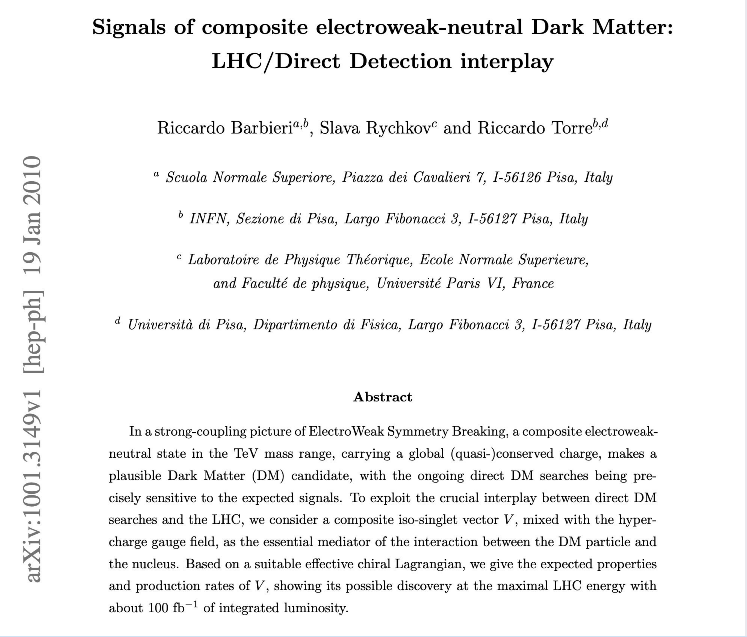

arXiv:1001.3149v1 [hep-ph] 19 Jan 2010

Signals of composite electroweak-neutral Dark Matter: LHC/Direct Detection interplay

Riccardo Barbieri[a,b], Slava Rychkov[c] and Riccardo Torre[b,d]

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Abstract

In a strong-coupling picture of ElectroWeak Symmetry Breaking, a composite electroweak-neutral state in the TeV mass range, carrying a global (quasi-)conserved charge, makes a plausible Dark Matter (DM) candidate, with the ongoing direct DM searches being precisely sensitive to the expected signals. To exploit the crucial interplay between direct DM searches and the LHC, we consider a composite iso-singlet vector V, mixed with the hypercharge gauge field, as the essential mediator of the interaction between the DM particle and the nucleus. Based on a suitable effective chiral Lagrangian, we give the expected properties and production rates of V, showing its possible discovery at the maximal LHC energy with about 100 fb^{-1} of integrated luminosity.

A driving principle

<u>scientific revolutions are more often driven by new tools than by new concepts.</u>

Freeman J. Dyson, Birds and frogs, Selected Papers 1990-2014

A driving principle

The second theme that **George Green's work exemplifies is the** **historical fact that**

<u>scientific revolutions are more often driven by new tools than by new concepts</u>.

Thomas Kuhn in his famous **book, "The Structure of Scientific Revolutions",** talked almost exclusively about concepts and hardly at all about tools. His idea of a scientific revolution is based on a single example, the revolution in theoretical physics that occurred in the 1920s with the advent of quantum mechanics. This was a prime example of a concept-driven revolution. Kuhn's book **was so brilliantly** written **that** it became an instant classic. It **misled a whole generation of students and historians of science into believing that all scientific revolutions are concept driven.** The concept-driven revolutions are the ones that attract the most attention and have the greatest impact on public awareness of science, but in fact they are comparatively rare. **In the last five hundred years we have had six major concept driven revolutions, associated with the names of Copernicus, Newton, Darwin, Maxwell, Einstein and Freud, besides the quantum-mechanical revolution that Kuhn took as his model. During the same period there have been about twenty tool-driven revolutions, not so impressive to the general public but of equal importance to the progress of science.** I will not attempt to make a complete list of tool-driven revolutions. Two prime examples are the Galilean revolution resulting from the use of the telescope in astronomy, and the Crick–Watson revolution resulting from the use of X-ray diffraction to determine the structure of big molecules in biology. **The effect of a concept-driven revolution is to explain old things in new ways. The effect of a tool-driven revolution is to discover new things that have to be explained.** In physics there has been a preponderance of tool-driven revolutions. We have been more successful in discovering new things than in explaining old ones. **George Green's great discovery, the Green's function, is a mathematical tool rather than a physical concept. It did not give the world a new theory of electricity and magnetism or a new picture of physical reality. It gave the world a new bag of mathematical tricks**, useful for exploring the consequences of theories and for predicting the existence of new phenomena that experimenters could search for. The Green's function was **a tool of discovery, like the telescope and the microscope, but aimed at mathematical models and theories instead of being aimed at the sky and the microbe.**

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Preview

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Fundamental Physics

Machine Learning

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Fundamental Physics

Objective: describe all known particles, their interactions, and at all scales

Machine Learning

Objective: emulate human intelligence to allow machines to perform tasks without explicitly programming them

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Machine Learning

Objective: describe all features, their interactions (correlations), and at all scales (context)

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Energy

G_N^{-2} EFT close to the Planck scale (quantum gravity, string theory, bla bla bla)

EFT above the EW scale (SMEFT)

EFT at the EW scale (dim-4 Standard Model)

G_F^{-2}

EFT below EW scale (QED+QCD+Fermi Theory)

$\Lambda_{\rm QCD}$ EFT below QCD scale (QED + Chiral QCD+Fermi Theory)

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EFT below electron mass (Euler-Heisenberg)

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Context Complexity / Correlation length

Fully connected graph data / Unlimited range
Transformers, Self-Attention, GATs: Maximum flexibility, allowing global dependencies across all points in the input

Sparse graph data - Extended range
Graph NN (GNN): Variable-length, structured data with complex dependencies and structured relationships

Grids/sequences - Finite range
Convolutional NN (CNNs), Recursive NNs (RNN), etc: structured spatial or sequential data, capturing local patterns but with limited range

Vector data - Moderate Range
Feedforward Neural Networks (FFNNs): Fixed-length vectors, capturing shallow dependencies within small data sets

Scalar Data - Short Range
Associative Memory Models, Hopfield Networks, Perceptrons: minimal complexity, point-wise or isolated associations

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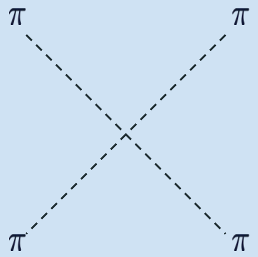

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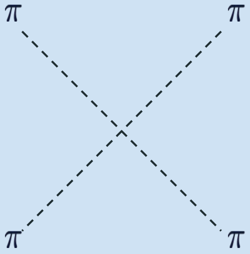

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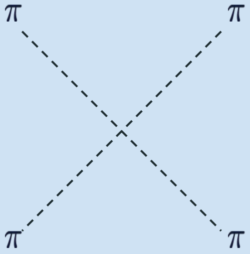

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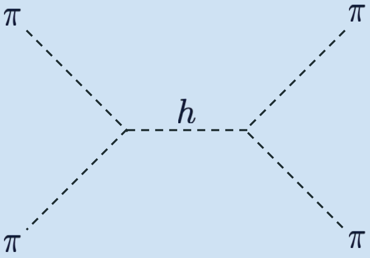

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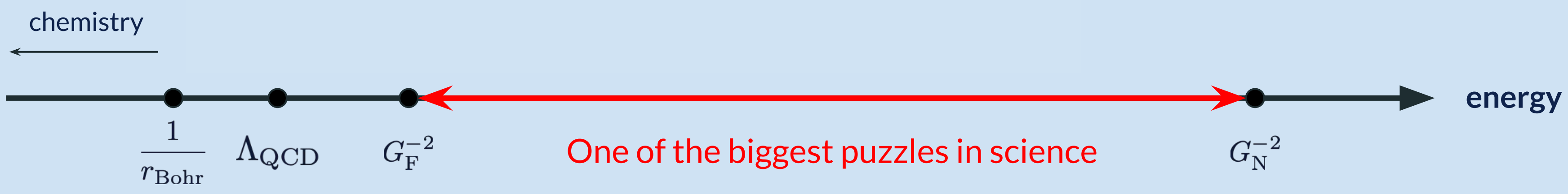

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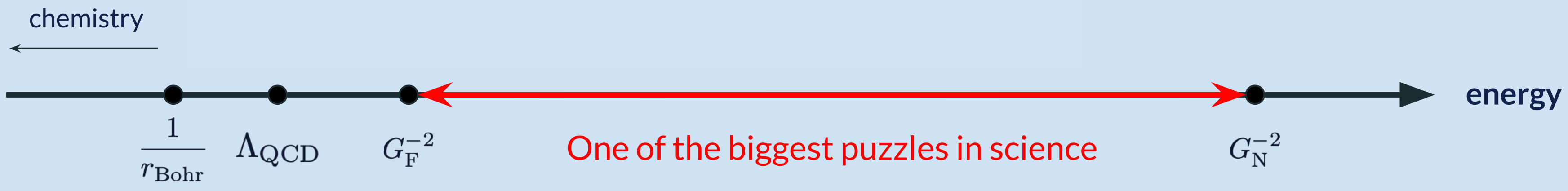

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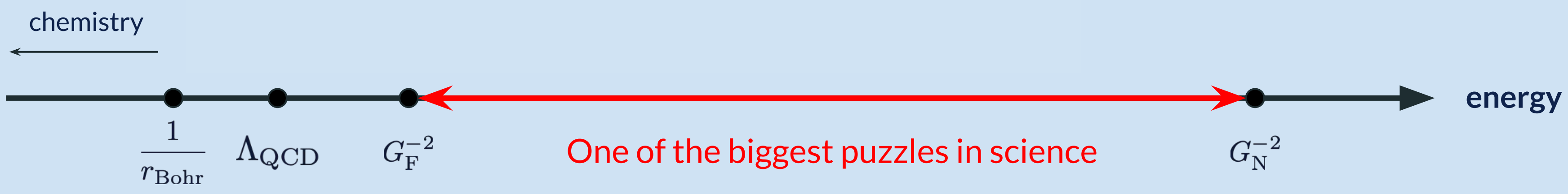

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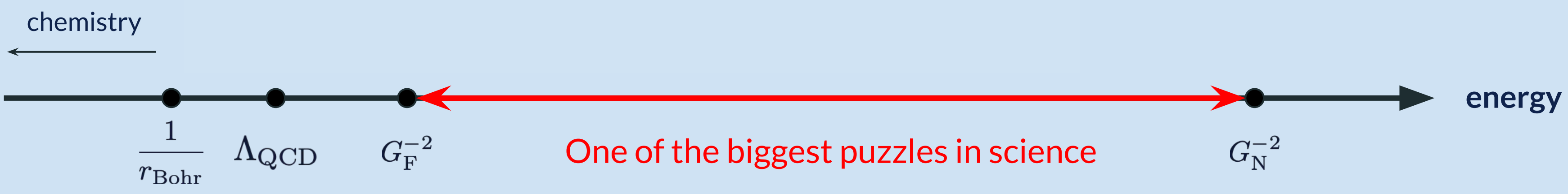

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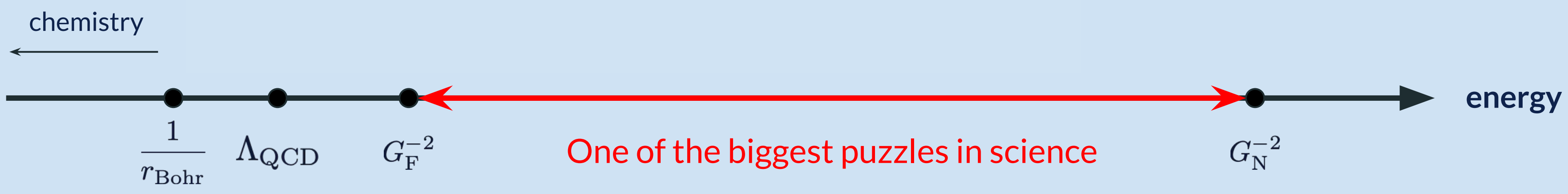

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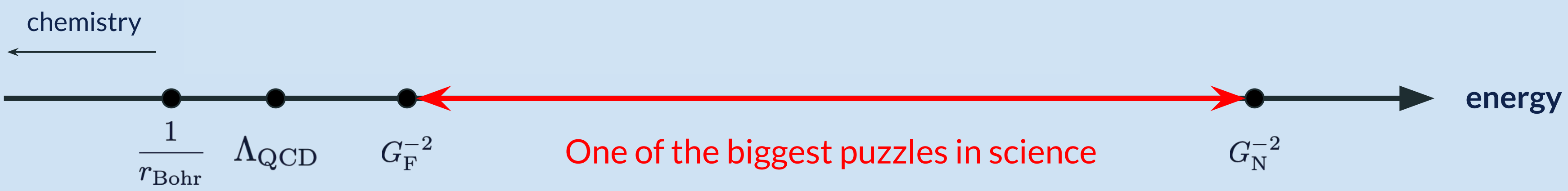

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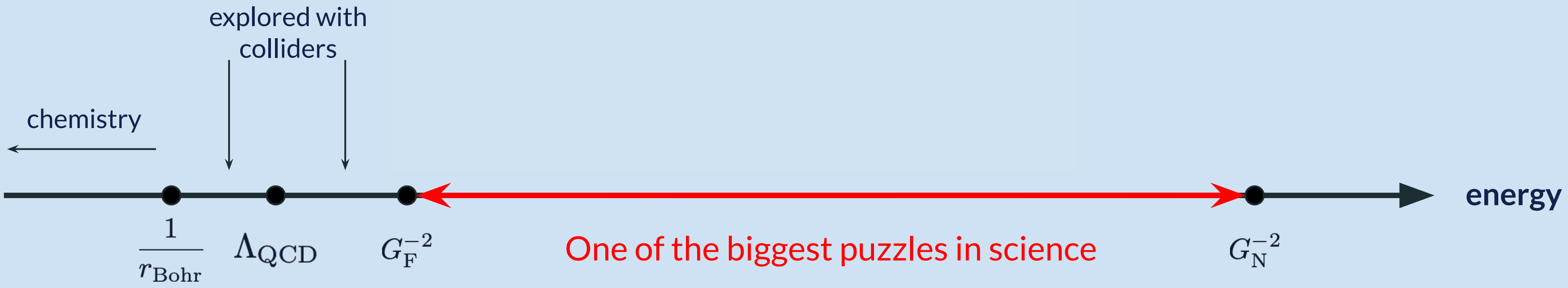

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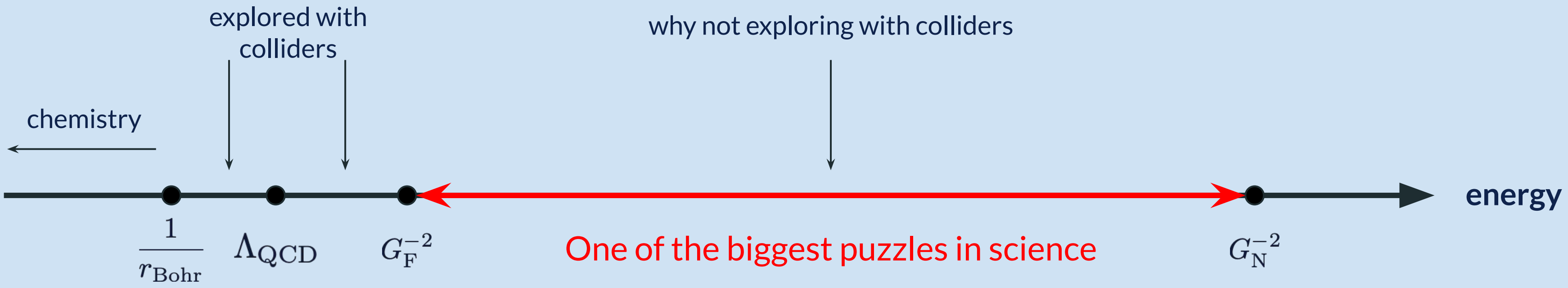

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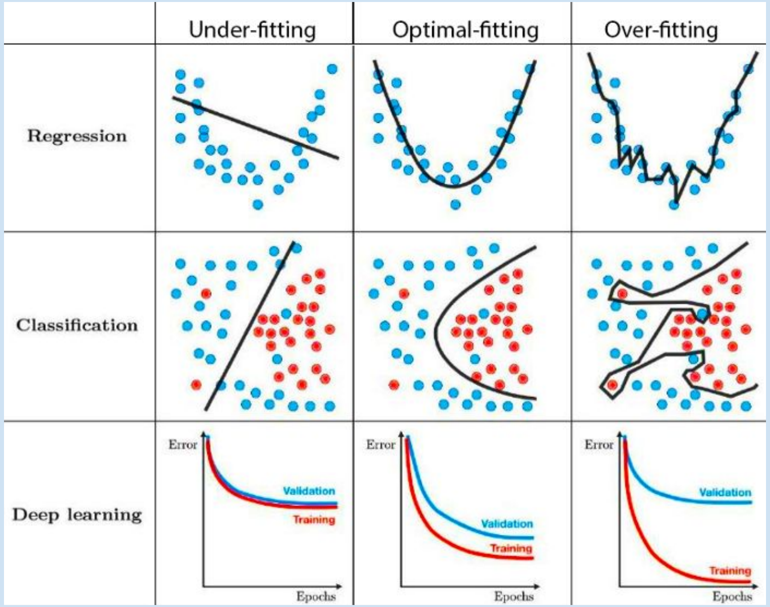

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All the difficulty of ML is handling complicated dependencies that allow to capture higher-order, long-range correlations in data of arbitrary representation and dimension

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Perceptron vs neuron

Input vector of features

Weights vector

Bias

$$f(\boldsymbol{x}) = \sigma(\boldsymbol{w} \cdot \boldsymbol{x} + b)$$

Perceptron: Heaviside activation
Neuron: more general activation

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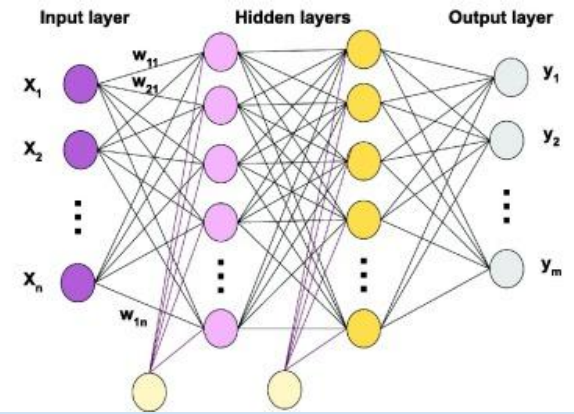
Multilayer perceptron (feedforward Neural Network)



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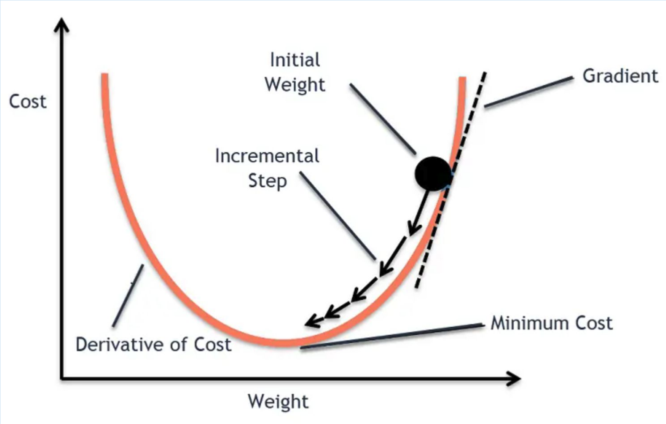

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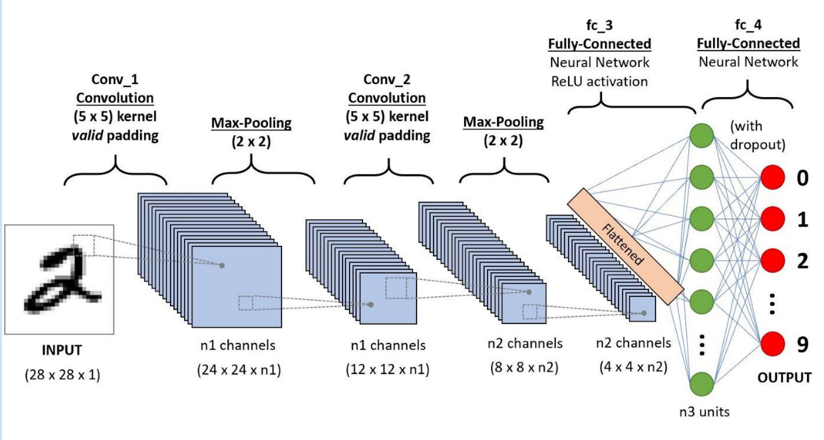

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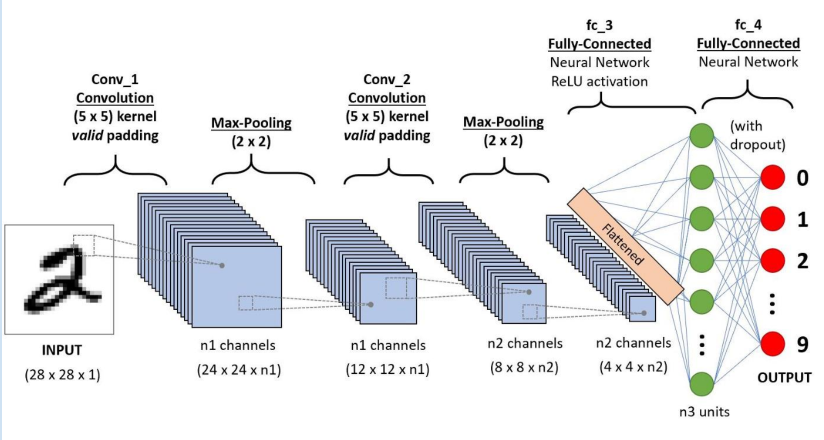

Convolutional filter

Convolution: $$Y_{i,j} = \sum_m \sum_n X_{i+m,j+n} \cdot K_{m,n} + b$$

Activation: $$Y'_{i,j} = \sigma(Y_{i,j})$$

Pooling (2x2): $$P_{i,j} = \max(Y'_{i,j}, Y'_{i+1,j}, Y'_{i,j+1}, Y'_{i+1,j+1})$$

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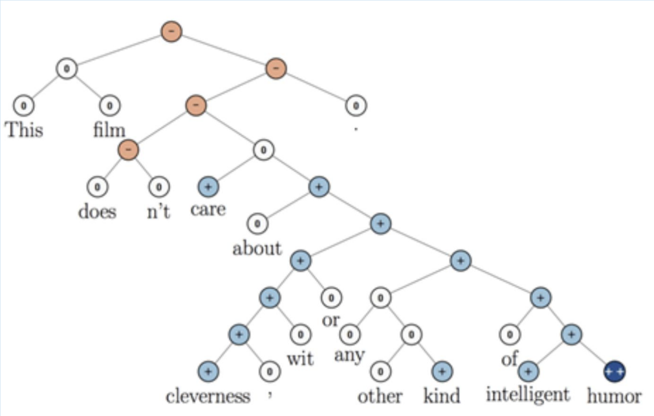

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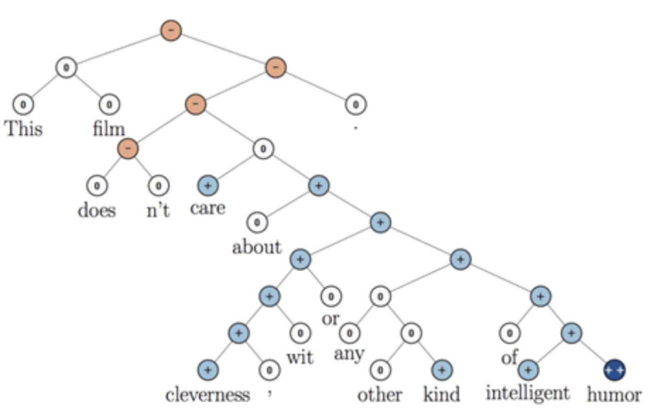

Hidden state update: $\boldsymbol{h}_t = \sigma(W_h \boldsymbol{h}_{t-1} + W_x \boldsymbol{x}_t + \boldsymbol{b})$

Output update: $\boldsymbol{y}_t = f(\boldsymbol{h}_t)$

Over long sequences it suffers from vanishing or exploding gradients, which limits the correlation length

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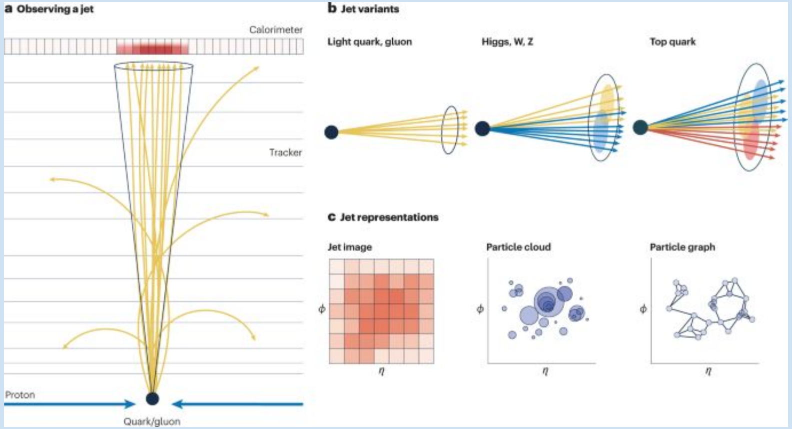

- GNN particularly suited for particle physics applications
- Clouds of particles with related observables naturally represented as graphs
- Great improvements in tagging and reconstruction

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- Only model able to catch long-range correlations (e.g. ChatGPT)

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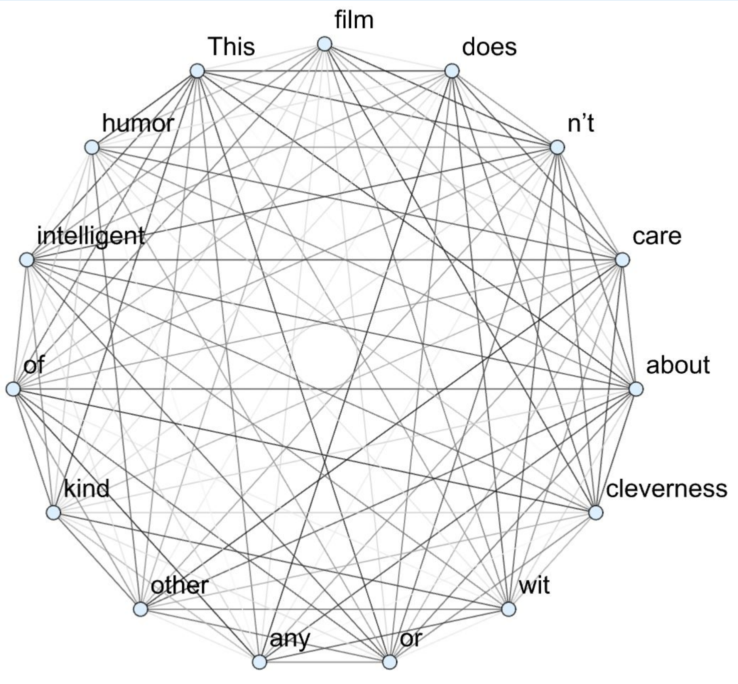

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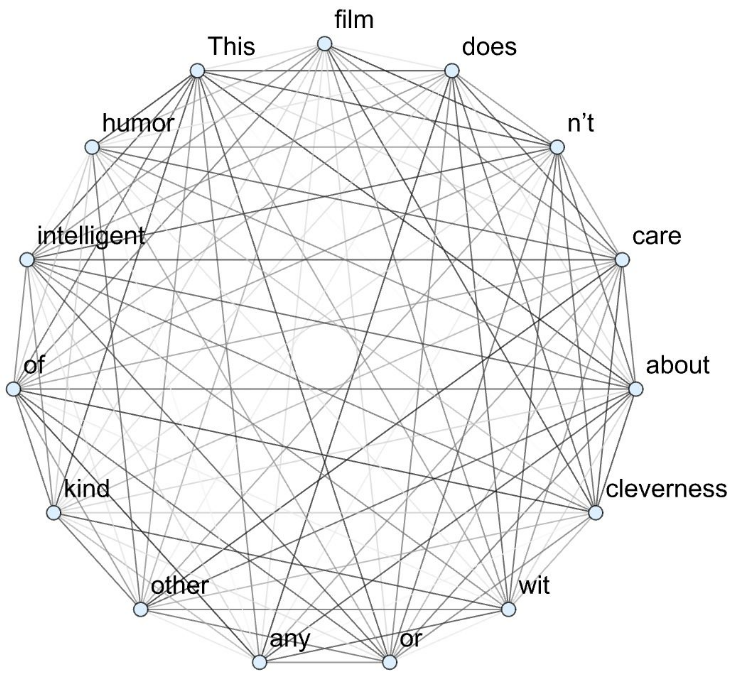

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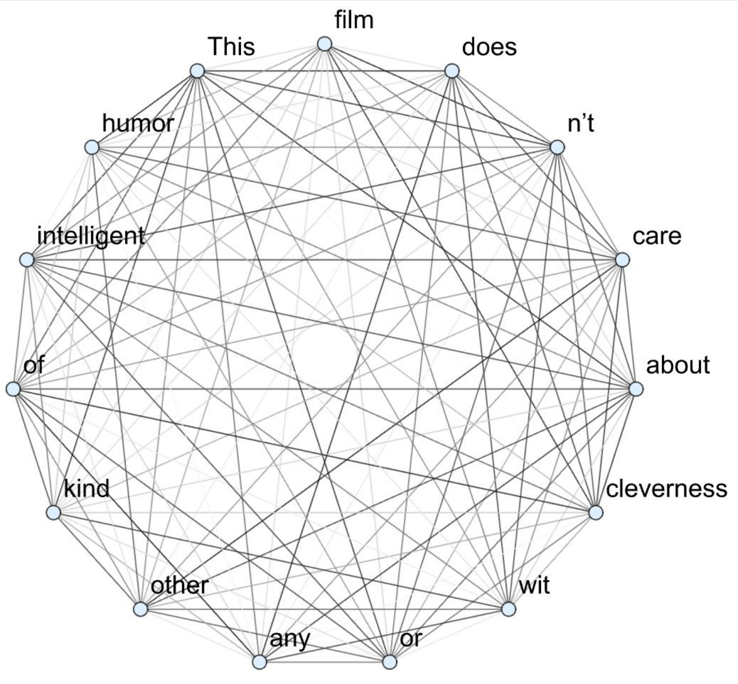

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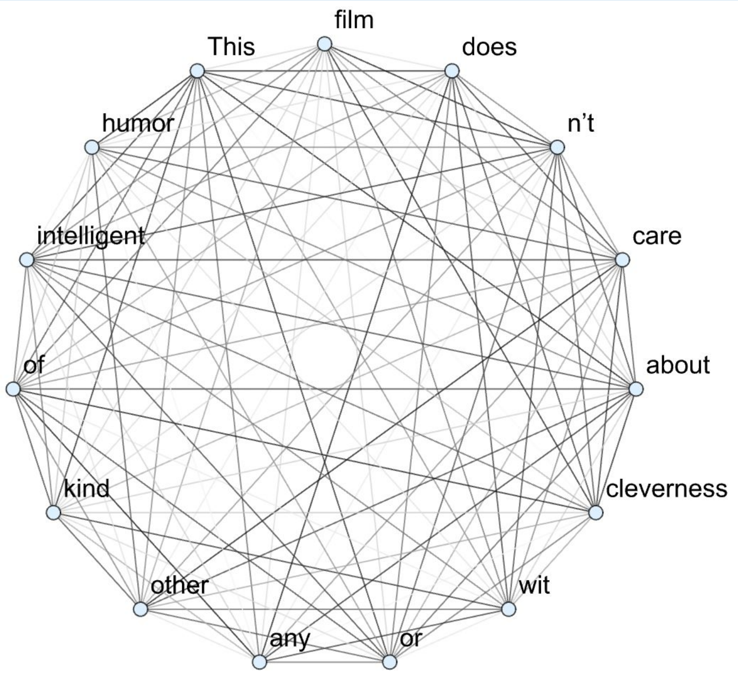

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- This idea, at the basis of Transformers, has revolutionized ML, allowing to extend the correlation range that NNs are able to capture

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  - Monte Carlo simulations
  - Detector design
  - Detector operation
  - Data collection
  - Data analysis
  - Physics interpretation and hypothesis testing

Why HEP should care about ML

- HEP is the scientific field of science that produces and needs to analyse the largest amount of data, both real and synthetic (Monte Carlo)
- ML can find application in each step of the HEP Workflow
  - Precision calculations
  - Monte Carlo simulations
  - Detector design
  - Detector operation
  - Data collection
  - Data analysis
  - Physics interpretation and hypothesis testing
- Thanks to the technologies I discussed earlier, ML has been shown to be able to improve over traditional techniques in all of these tasks

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  - Analogy of the faced problems as stressed in this talk

Challenges

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ML is mostly developed "by companies for companies"

This raises some issues that also represent the biggest challenges

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- Data representation
- Precision
- Evaluation

Choosing the right representation

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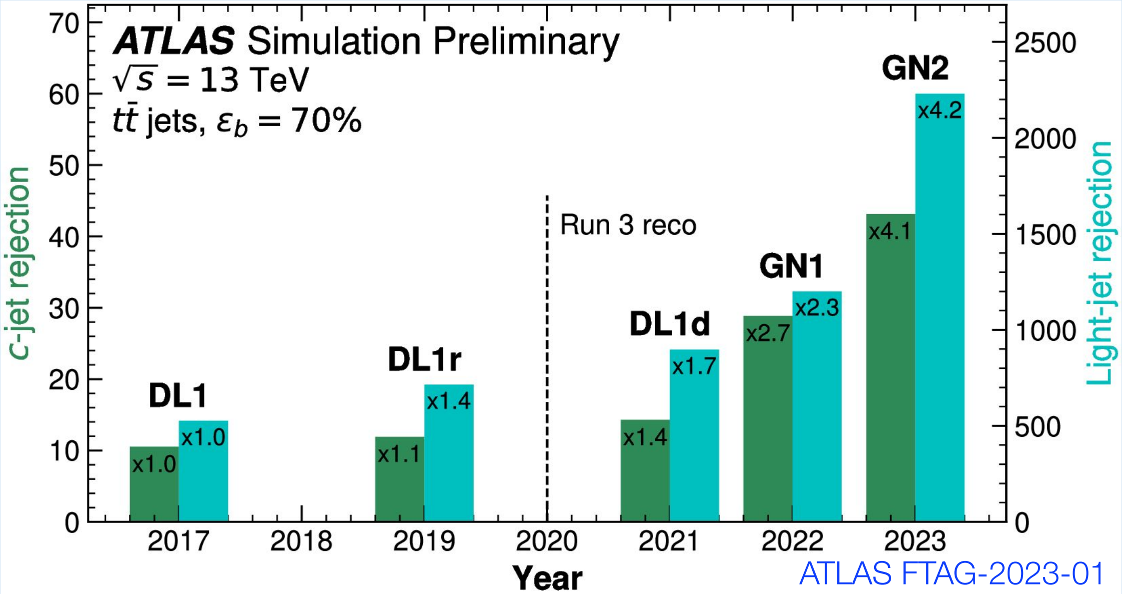

Factor of 4x in 4 years, a tool-induced "revolution" in HEP!

Choosing the right representation (graphs) together with implementing "attention" let to an impressive improvement

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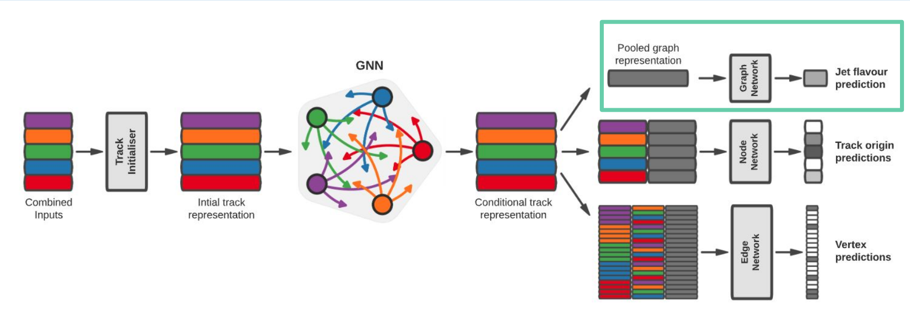

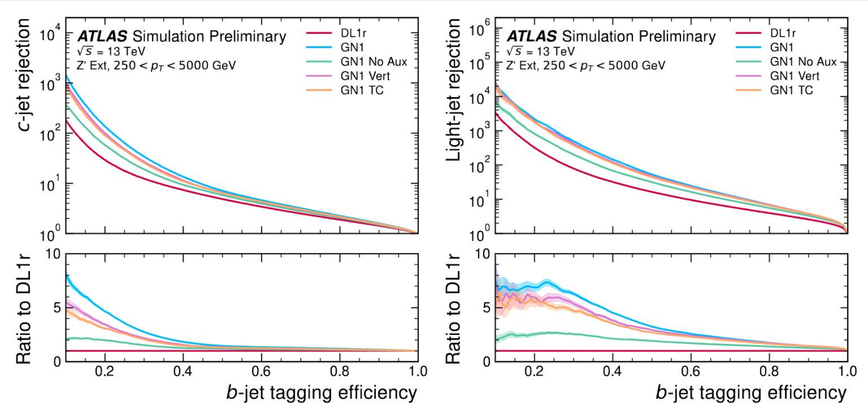

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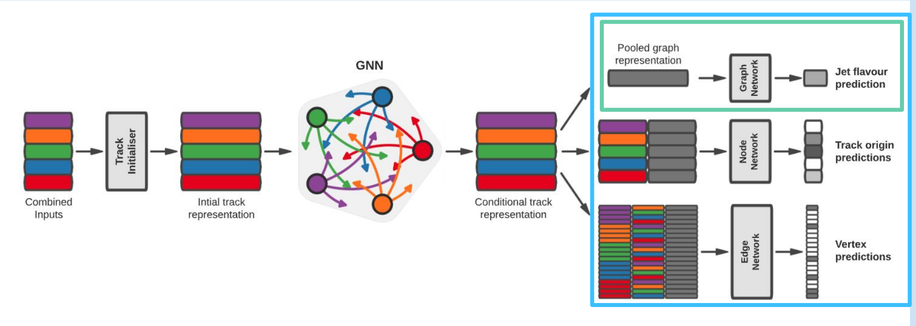

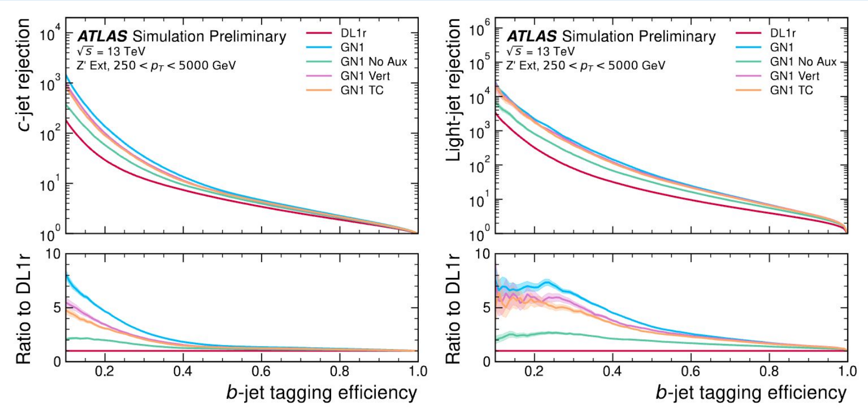

Developing robust evaluation

Developing robust evaluation

Refereeing the Referees: Evaluating Two-Sample Tests for Validating Generators in Precision Sciences

Samuele Grossi[a,b], Marco Letizia[b,c], and Riccardo Torre[a,b]

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September 26, 2024

arXiv:2409.16336v1 [stat.ML] 24 Sep 2024

Abstract

We propose a robust methodology to evaluate the performance and computational efficiency of non-parametric two-sample tests, specifically designed for high-dimensional generative models in scientific applications such as in particle physics. The study focuses on tests built from univariate integral probability measures: the sliced Wasserstein distance and the mean of the Kolmogorov-Smirnov statistics, already discussed in the literature, and the novel sliced Kolmogorov-Smirnov statistic. These metrics can be evaluated in parallel, allowing for fast and reliable estimates of their distribution under the null hypothesis. We also compare these metrics with the recently proposed unbiased Fréchet Gaussian Distance and the unbiased quadratic Maximum Mean Discrepancy, computed with a quartic polynomial kernel. We evaluate the proposed tests on various distributions, focusing on their sensitivity to deformations parameterized by a single parameter ϵ. Our experiments include correlated Gaussians and mixtures of Gaussians in 5, 20, and 100 dimensions, and a particle physics dataset of gluon jets from the JetNet dataset, considering both jet- and particle-level features. Our results demonstrate that one-dimensional-based tests provide a level of sensitivity comparable to other multivariate metrics, but with significantly lower computational cost, making them ideal for evaluating generative models in high-dimensional settings. This methodology offers an efficient, standardized tool for model comparison and can serve as a benchmark for more advanced tests, including machine-learning-based approaches.

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- Validate results on physics datasets (gluon jets with both jet and particle-level information)

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- ML is not "just for experimentalists", as it is not just a practical tool
- The role of theorists is essential, as it was in understanding how to use Green's function to explain physical phenomena

Thank you for your attention!

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And thanks Riccardo for his mentorship and inspiration!

Auguri!