Machine Learning in Particle Physics

Energy and Intensity Frontiers

Ahmed Ali Abdelalim

Zewail City of Science and Technology, Giza, Egypt.
Physics Department, Faculty of Science, Helwan University, Cairo, Egypt.

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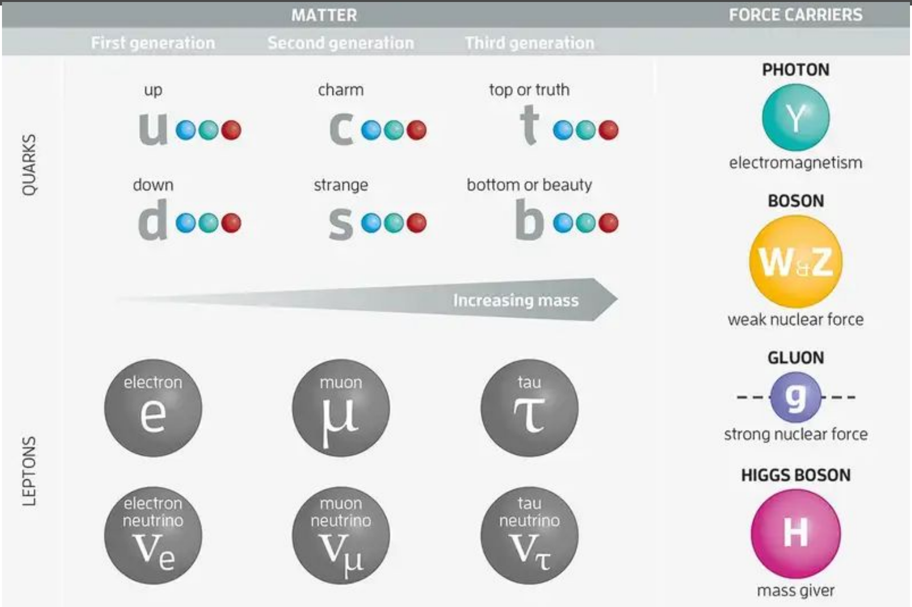
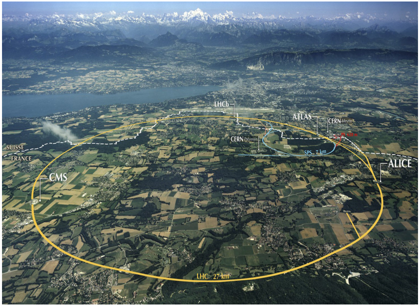
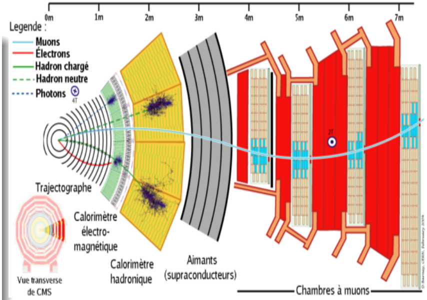
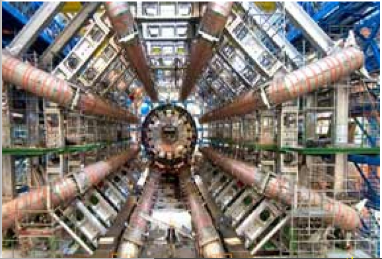
The Standard Model's success and limitations



LHC, ATLAS, and CMS





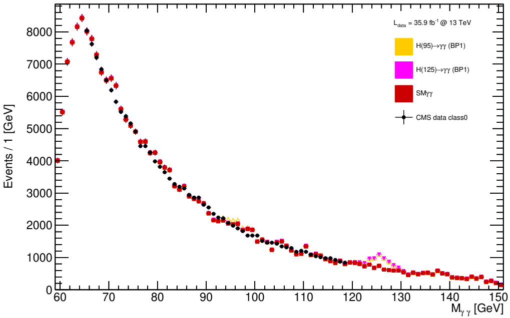


- LHC data generation and challenges : CERN Data Centre stores more than 30 PB/year from the LHC experiments, enough to fill about 1.2 M Blu-ray discs, i.e. 250 years of HD video.
- Data reduction strategies using ML.

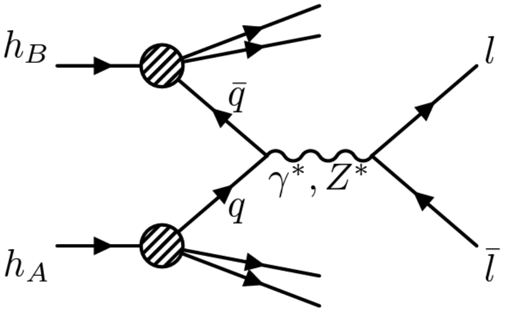
Parameter Estimation

Conduct a chain of Monte Carlo simulations to theoretically predict the outcomes of signal and background processes for specific distributions. Design a set of selection cuts to enhance the signal-to-background ratio $(N_s/\sqrt{N_b})$.

- di-photon with $|\eta^{\gamma}| \leqslant 2.5$ and out of the crack region between the barrel and end-cap parts of the CMS EM-calorimeters.
- p_T leading photon in the pair has to have $p_T^{\gamma_1}/M_{\gamma\gamma} > 30.6/65.0 = 0.47$.
- p_T next-leading photon in the pair has to have $p_T^{\gamma_2}/M_{\gamma\gamma} > 18.2/65.0 = 0.28$.



Event Generation



$$\sigma_{AB} = \int dx_q dx_{\bar{q}}\, f_{q/A}(x_q)\, f_{\bar{q}/B}(x_{\bar{q}})\, \hat{\sigma}(q\bar{q} \to \mu^+\mu^-) \tag{1}$$

$$\sigma_{AB} = \int dx_q dx_{\bar{q}}\, f_{q/A}(x_q, Q^2)\, f_{\bar{q}/B}(x_{\bar{q}}, Q^2)\, \hat{\sigma}(q\bar{q} \to \mu^+\mu^-) \tag{2}$$

$$\sigma_{AB} = \int dx_q dx_{\bar{q}}\, f_{q/A}(x_q, \mu_F^2)\, f_{\bar{q}/B}(x_{\bar{q}}, \mu_F^2) \left\{\hat{\sigma}_0 + \alpha_s(\mu_R^2)\hat{\sigma}_1 + \ldots\right\}_{q\bar{q}\to\mu^+\mu^-} \quad (3)$$

- σ_{AB} : Hadronic cross-section for the process.
- x_q, $x_{\bar{q}}$: Momentum fractions of the quark and antiquark from hadrons A and B, respectively.
- $f_{q/A}(x_q)$, $f_{\bar{q}/B}(x_{\bar{q}})$: Parton distribution functions (PDFs) representing the probability density to find a quark q with momentum fraction x_q in hadron A, and an antiquark $\bar{q}$ with momentum fraction $x_{\bar{q}}$ in hadron B.
- $\hat{\sigma}(q\bar{q} \to \mu^+\mu^-)$: Partonic cross-section for the process where a quark-antiquark pair annihilates to produce a muon pair.
- Q^2 : Large momentum scale characterizing the hard scattering process (e.g., the invariant mass of the muon pair).
- μ_F : Factorization scale separating long- and short-distance physics.
- $\alpha_s(\mu_R^2)$: Strong coupling constant evaluated at the renormalization scale μ_R.
- $\hat{\sigma}_0, \hat{\sigma}_1$: Partonic cross-sections at leading order (LO) and next-to-leading order (NLO), respectively.
- μ_R : Renormalization scale at which the strong coupling constant α_s is evaluated.

Particle Reconstruction in the CMS Detector

The detector response to particles is simulated using MC to predict the detector's performance under various conditions.
The simulation relies on several key parameters :

- L : Luminosity of the collisions (e.g., $10^{34}\,\mathrm{cm}^{-2}\mathrm{s}^{-1}$).
- $\sqrt{s}$: Center-of-mass energy of the proton-proton collisions (e.g., 14 TeV).
- η : Pseudorapidity, defined as $\eta = -\ln\tan(\theta/2)$, where θ is the polar angle.
- p_T : Transverse momentum of the particle.
- ΔR : Separation distance in the $\eta - \phi$ space, $\Delta R = \sqrt{(\Delta\eta)^2 + (\Delta\phi)^2}$.

CMS Trigger System

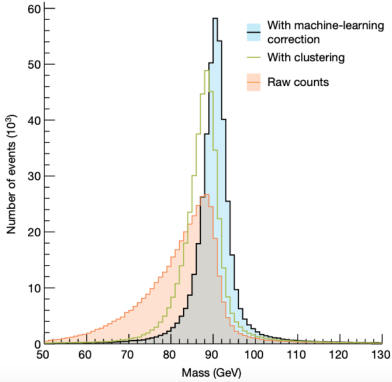
- **LHC Collision Rate :**
  - Proton-proton collisions occur at a rate of **40 MHz** (one collision every 25 ns).
- **Trigger Levels :**
  - **Level-1 (L1) Trigger :**
    - Initial reduction of the collision rate from **40 MHz to 100 kHz**.
    - Achieved using fast, custom-designed hardware processing calorimeter and muon chamber data.
  - **High-Level Trigger (HLT) :**
    - Further reduction of the rate from **100 kHz to 40 Hz**.
    - Utilizes sophisticated software algorithms running on a computing farm.
- **Trigger Objects and Input :**
  - Electrons, photons, muons, hadronic jets, τ jets.
  - Total and missing transverse energies (E_T), scalar E_T sum, jet multiplicities.
- **Trigger Architecture :**
  - Hierarchical design with three layers : local, regional, and global.
  - Global Calorimeter and Global Muon Trigger evaluate events and send selected ones to the HLT for detailed processing.

Enhancing Efficiency with Machine Learning

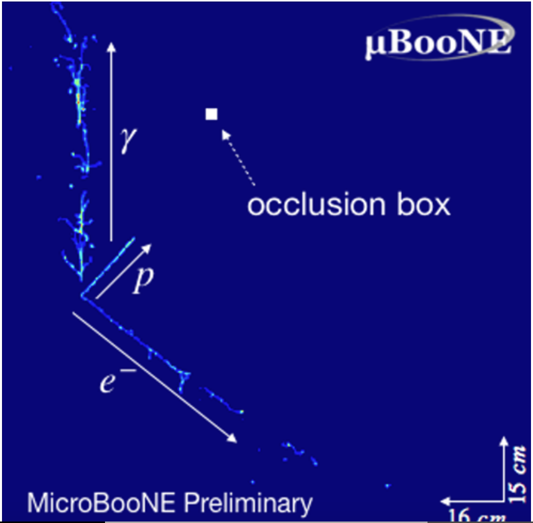
In every step of the process—object reconstruction, event reconstruction, and triggers—there are inefficiencies. Although individually small, these inefficiencies add up and can become significant. This can be improved by using machine learning techniques instead of traditional methods.

Common Tasks of Machine Learning Tools in HEP

- **Event Classification (determining particle properties) :**
  - Distinguishing signal events (e.g., Z or H boson production) from background events.
  - Example : Use of Boosted Decision Trees (BDTs) or Neural Networks (NNs) for classification tasks.



- **Particle Identification :**
  - Identifying types of particles (e.g., electrons, muons, quarks) from detector data.
  - Techniques : Convolutional Neural Networks (CNNs) for image-like data from calorimeters.



- **Regression Tasks :**
  - Estimating continuous parameters like energy, momentum, or mass of particles.
  - Example : Using regression algorithms to calibrate detector responses.
- **Anomaly Detection :**
  - Identifying rare or unexpected events that deviate from the known Standard Model processes.
  - Methods : Autoencoders, unsupervised learning techniques.
- **Data Generation and Simulation :**
  - Generating synthetic datasets to simulate collision events.
  - Example : Generative Adversarial Networks (GANs) to produce realistic events for training purposes.

Thank You...