Machine Learning Methods for Top Quark Reconstruction

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INTRODUCTION

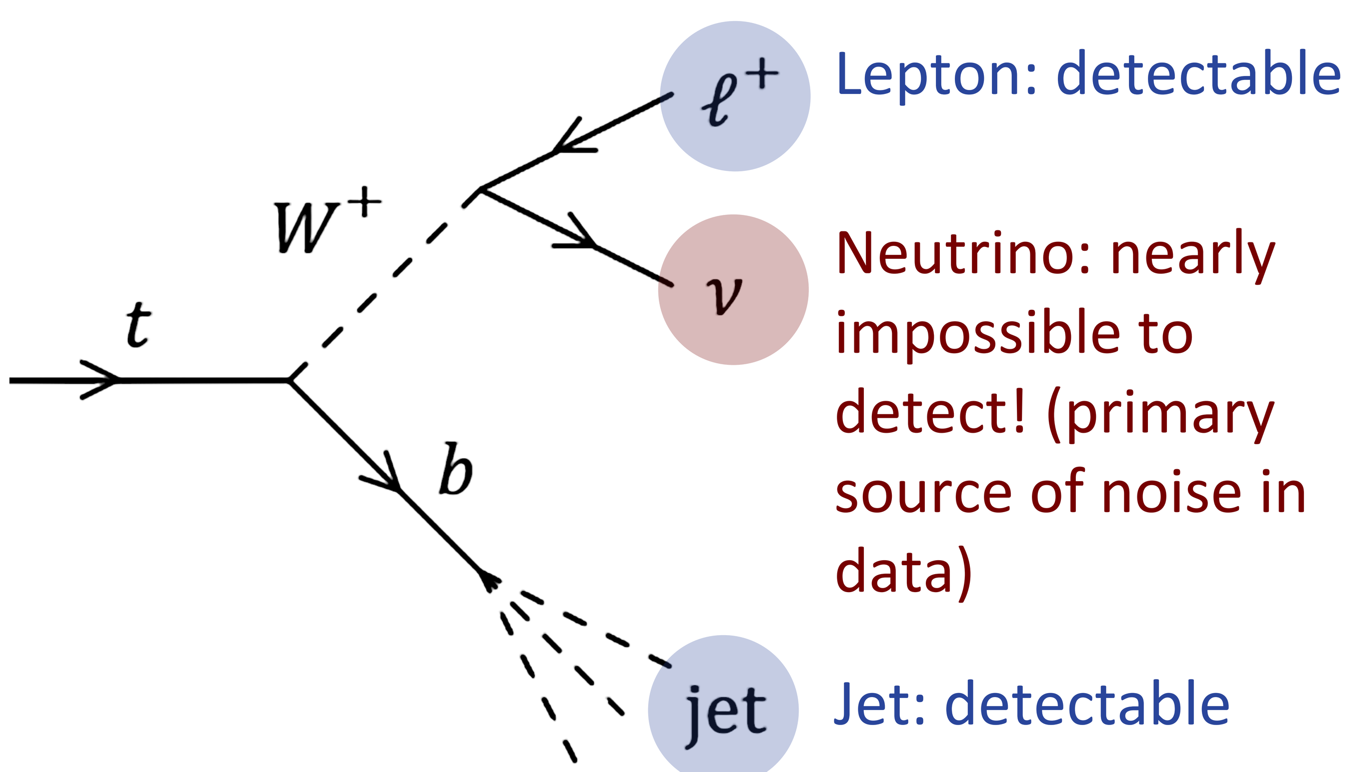
Top quarks are **elementary particles**. They are:

- Short-lived, with mean lifetime $<10^{-24}$ s
- Extremely rare, only produced in accelerators
- The most massive fundamental particle
- Discovered relatively recently (1995)

We use machine learning to improve the characterization of **quantum entanglement of top quark pairs** using data from the LHC's Compact Muon Solenoid (CMS) detector.

PHYSICS

- Top quarks are **generated in entangled particle-antiparticle pairs**
- Because top quarks decay so rapidly, their **entanglement information is encoded in the kinematics of their decay products**



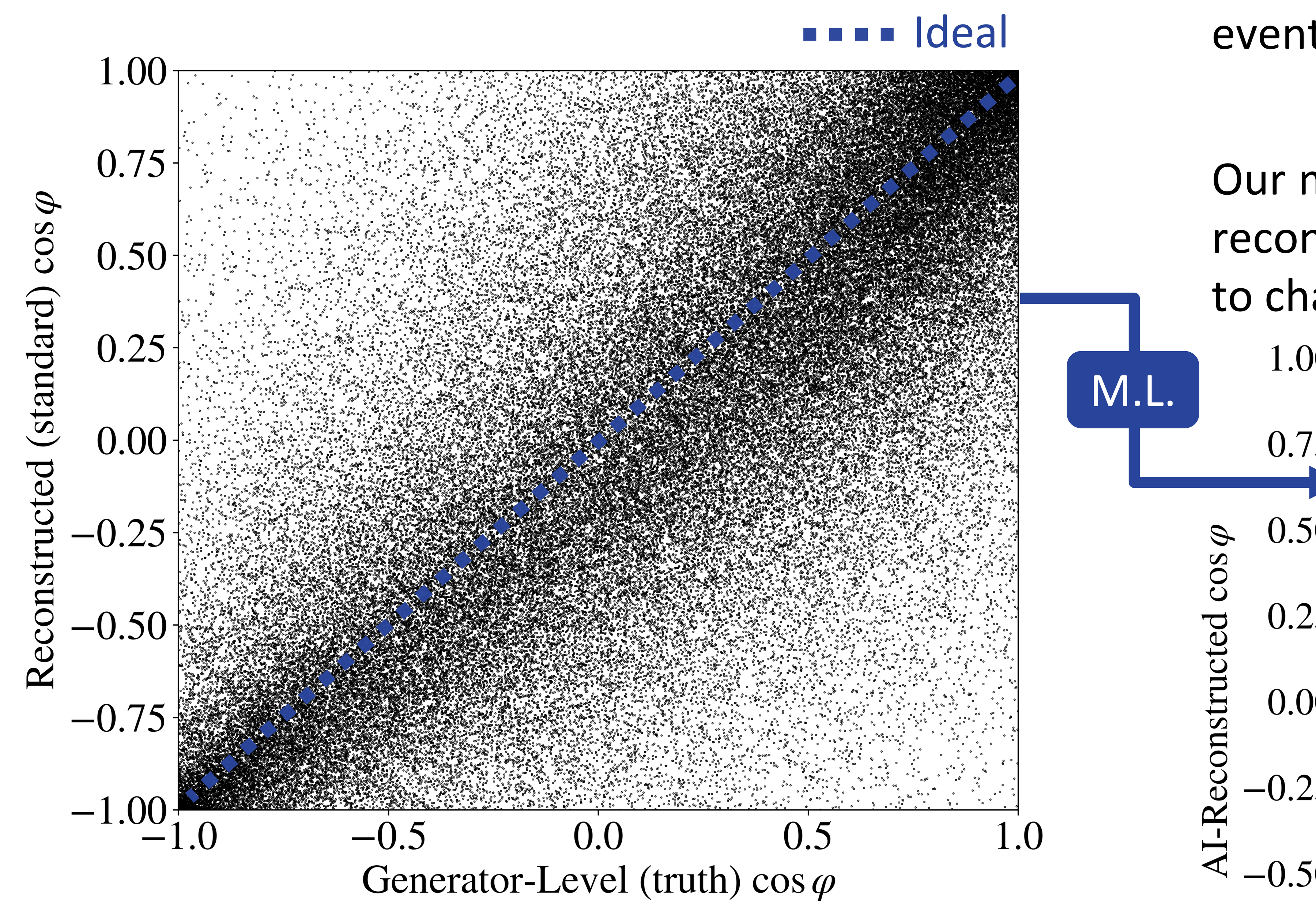
We recover (dilepton channel) top entanglement as a function of top-antitop invariant mass by analyzing the **angular distribution of leptons Lorentz boosted into their tops' parent frames**. This distribution has a differential cross-section of the form:

$$\frac{1}{\sigma}\frac{d\sigma}{d\cos\varphi} = \frac{1}{2}\left(1 + \frac{1+\delta}{3}\cos\varphi\right)$$

Where φ is the angular separation between leptons and $\delta > 0$ is a sufficient condition for entanglement *(Afik & De Nova, 2021)*.

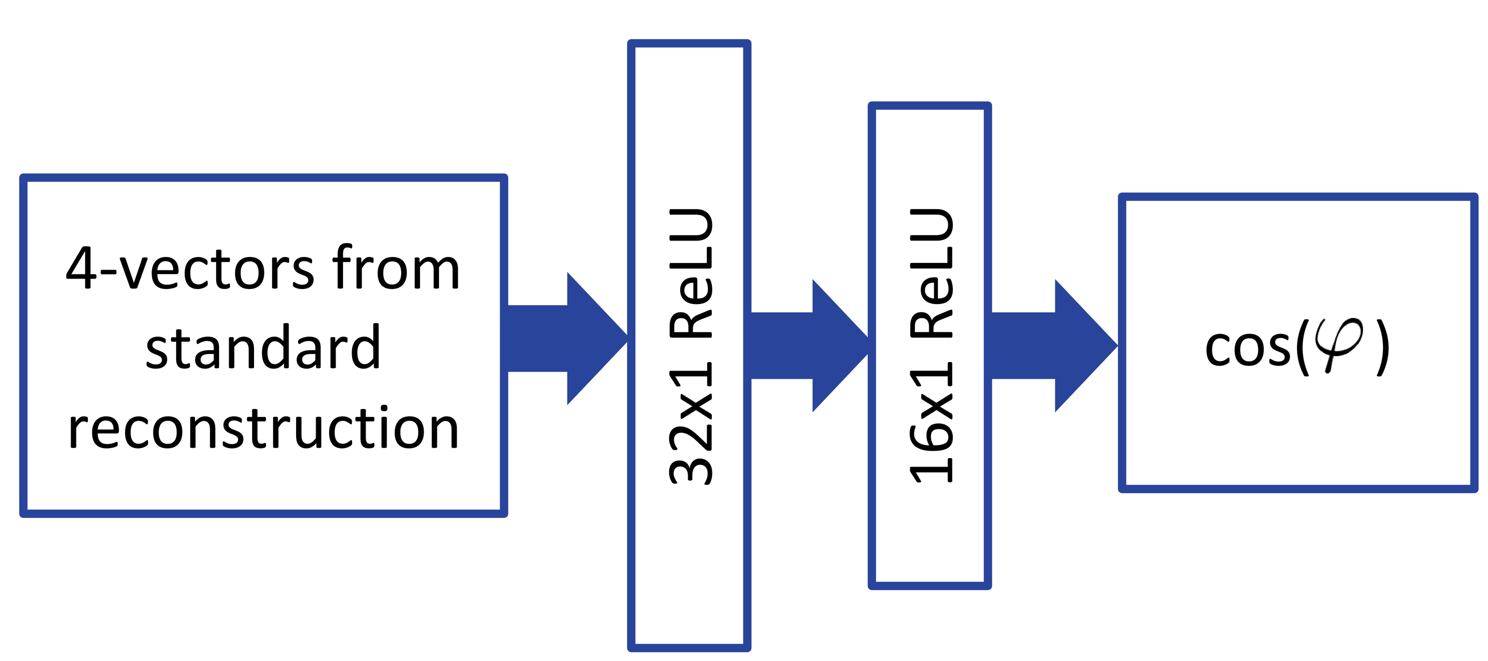
CHALLENGE

- Top quarks decay into **detection-evading neutrinos**, making our reconstruction of top momentum poor.
- This means we can't accurately determine φ and measure top entanglement.
- This plot shows a reconstruction of φ using the standard LHC's standard techniques (a perfect reconstruction would yield a **straight line**):



METHODOLOGY

To improve the accuracy of our reconstruction, we **augment the reconstruction process with a shallow artificial neural network.** The network's architecture is nothing more than dense, ReLU-activated layers:



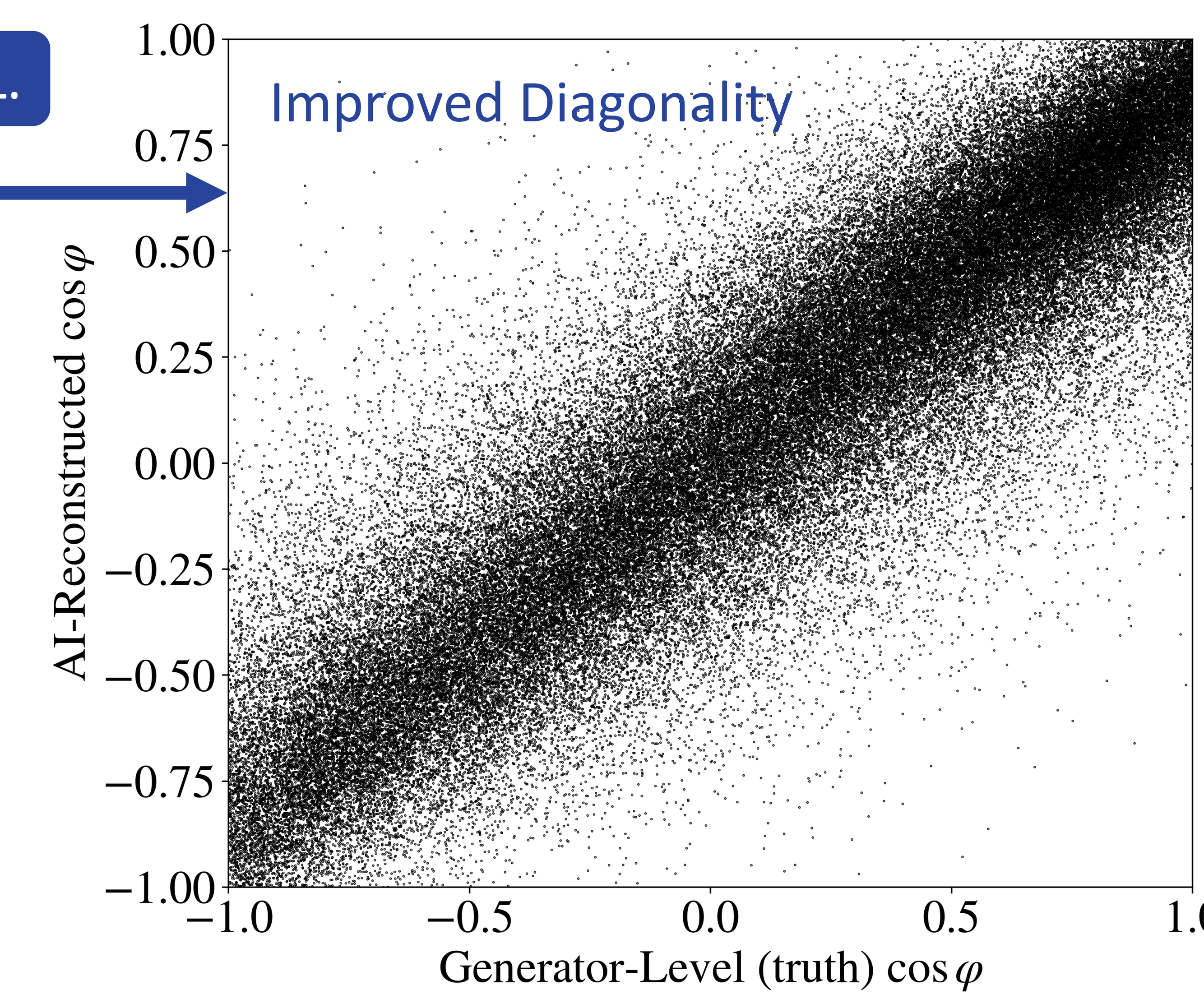
Our loss function is MSE in the output, and we use the Adam stochastic optimization algorithm.

DATA

As per standard procedure in high-energy particle physics analyses, we first run our network on simulated Monte Carlo data generated by the CMS Group. Our complete dataset contains ~10^6 events (samples) partitioned with an 8:1:1 training-test-validation split. Additionally, we limit our analysis to *ee* (electron-positron pair) events.

RESULTS

Our method showed a significant improvement in reconstruction of the cos(φ) distribution required to characterize entanglement:



Our ML technique offers:

- A ~2x reduction in network residuals
- Significantly fewer outliers
- Ultimately, improved accuracy in top quark entanglement characterization

FUTURE WORK

This method will be **applied to real CMS data**. Additionally, we plan to apply the noise-shaping abilities of neural networks (paired with analysis-specific loss functions) to improve analyses in other areas of particle physics.