

ARXIV REVIEW

ETP Meeting, May 13th, 2024
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Lam-Tung relation breaking in Z boson production as a probe of SMEFT effects – Xu Li, Bin Yan, C.-P. Yuan

- Angular distribution of leptons in Drell-Yan process expressed using harmonic polynomial with dimensionless coefficients:
 $A_0 = 4 - 10\langle \cos^2 \theta \rangle \implies A_2 = 10\langle \sin^2 \theta \cos 2\phi \rangle$ Lam-Tung relation (CS frame)
- Probes the polarization effects of Z, γ^*
- Valid up to $\mathcal{O}(\alpha_s)$ in perturbative QCD leading twist approximation
- Consequence of the spin-1/2 nature of the quarks at the tree-level and vector coupling feature of spin-1 gluon to quarks
- Breakign of relation from $\mathcal{O}(\alpha_s^2)$ confirmed by both the ATLAS and CMS due to non-coplanarity of parton and hadron planes at $\sqrt{s} = 8 \text{ TeV}$
- Deviation of ATLAS data from SM prediction at $\mathcal{O}(\alpha_s^2)$ in high- $p_T^{\ell\ell}$ region, theoretical calculations at $\mathcal{O}(\alpha_s^3)$ accuracy and NLO EW corrections, not non-perturbative effects

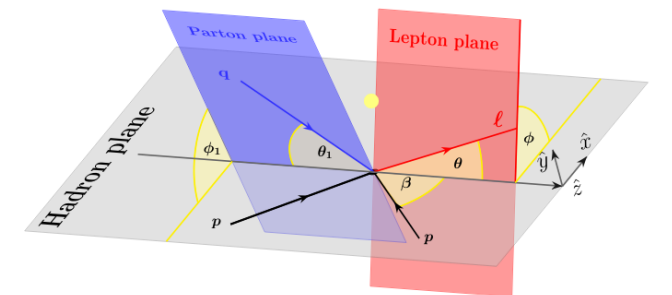
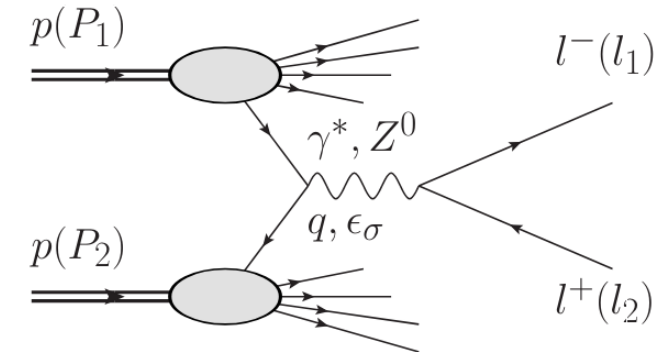
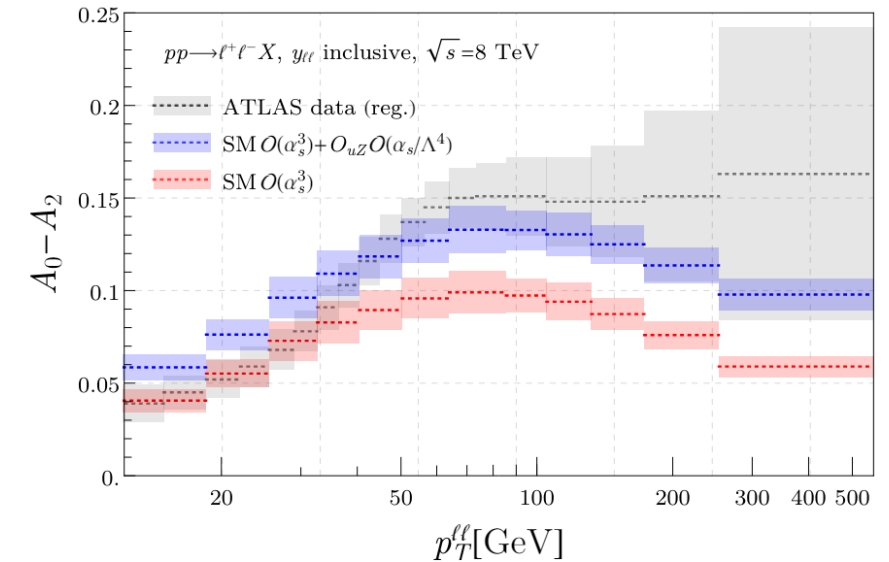


FIG. 1. The Collins-Soper frame, with planes of parton, leptons and hadrons causing the angular relation of eq. (5).

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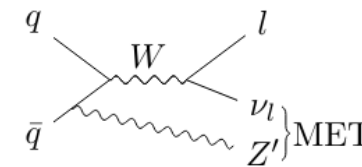
- Use of SMEFT to account for NP effects
- Quadratic effects from dim-6 $\mathcal{L}_{\psi^2 X \varphi}$ and $\mathcal{L}_{\psi^4}^{(2)}$ at $\mathcal{O}(1/\Lambda^4)$ and $\mathcal{O}(\alpha_s)$ accuracy in the coplanar case
- Linear effects from 7 dim-8 operators with same accuracy
- $\mathcal{L}_{\psi^2 X \varphi}$ contribution to scattering amplitude enhanced by $(M_Z/\Gamma_Z)^2$, only operator considered in the paper
- Search in $m_{\ell\ell} \in [80, 100] \text{ GeV}$ to neglect photon
- $\Lambda = 1 \text{ TeV}, \sqrt{s} = 8 \text{ TeV}$, one operator at a time, χ^2 analysis to constrain Wilson coefficients
- The current anomaly could be explained by \mathcal{O}_{uZ}
- It's a probe for NP independently of other NP effects even if in the future data are consistent with SM



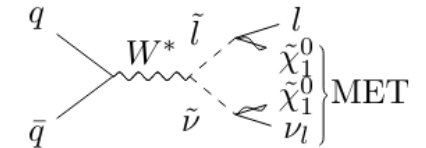
“Unification” of BSM Searches and SM Measurements: the case of lepton+MET and m_W

K. Agashe, S. Airen, R. Franceschini, D. Kim, A. V. Kotwal, L. Riccia, D. Sathyan

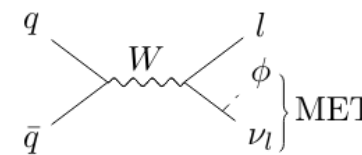
- NP produces kinematic distributions that are sufficiently different from the SM
- Requires a global fit to extract both with NP as nuisance parameters, example of m_W



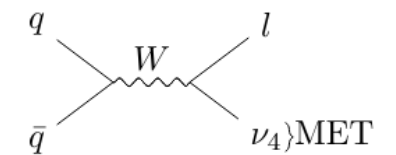
(a) Hadrophilic Z'



(b) MSSM slepton-sneutrino



(c) Neutrinophilic scalar



(d) Heavy neutrino

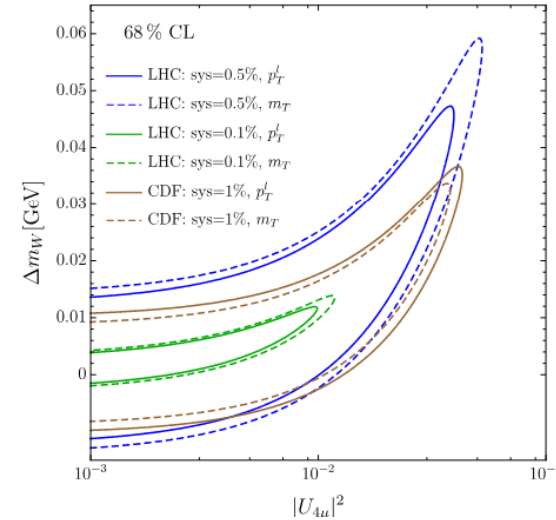
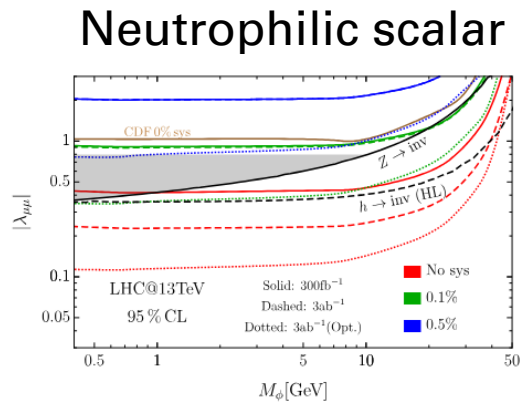
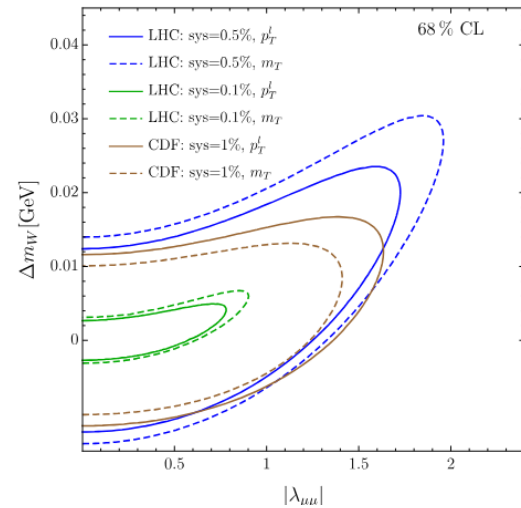
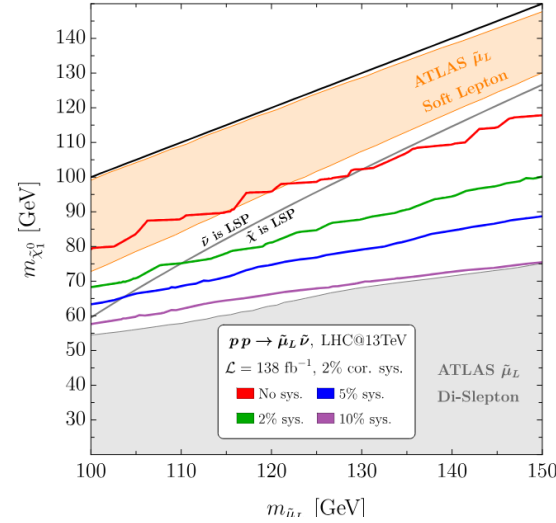
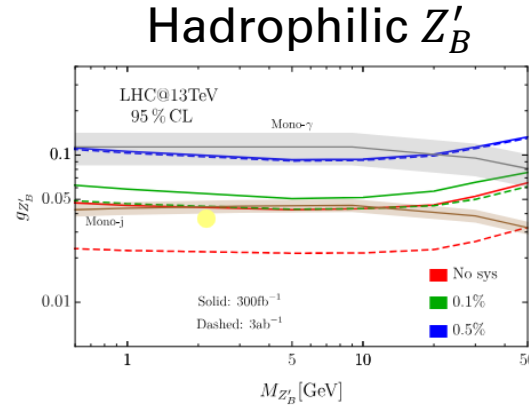
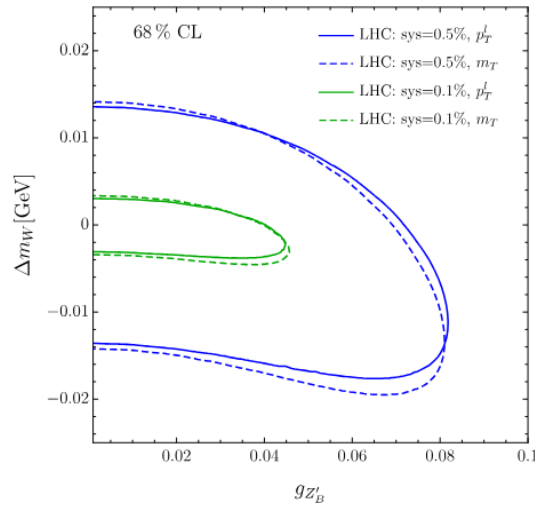
- MC simulations for ATLAS and CDF with $\ell = \mu$
- Backgrounds not included, supposed to be marginal
- $\Delta m_W = m_W - \overline{m_W}$, $\overline{m_W}$ mass in MC samples as substitute for data
- “sub-electroweak” region: $2p_T^\ell, m_T \leq m_W$ with small S/B and good control over uncertainties, selection following ATLAS and CDF
- “circa-electroweak” region for MSSM: $m_W \leq p_T^\ell, m_T \leq TeV, \Delta m_W = 0$

$$\chi^2_{\mathcal{O}}(\Delta m_W, \theta_{\text{NP}}) = \sum_{i,j=1}^{N_{\text{Bins}}} \left(\underbrace{N^i(\Delta m_W, \theta_{\text{NP}})}_{\substack{\text{Expected and observed} \\ \text{number of events}}} - \overline{N}^i \right) \underbrace{\Sigma_{ij}^{-1}}_{\substack{\text{NP parameter} \\ \text{Covariance matrix}}} \left(N^j(\Delta m_W, \theta_{\text{NP}}) - \overline{N}^j \right)$$

m_T, p_T^ℓ ATLAS, CDF + p_T^{miss}

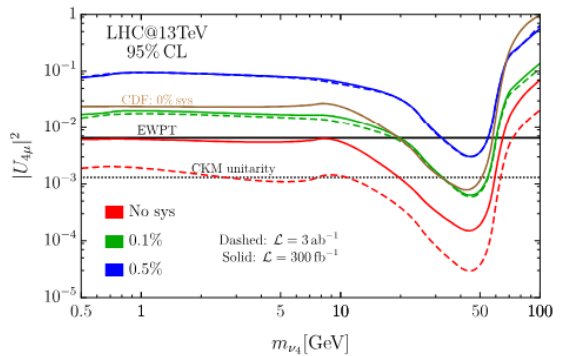
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MSSM slepton-sneutrino

Heavy neutrino



HEP ML Lab: An end-to-end framework for applying machine learning into phenomenology studies – Jing Li, Hao Sun [arXiv:2405.02888 \[hep-ph\]](https://arxiv.org/abs/2405.02888)

- Research involving machine learning models in high-energy physics comprises four steps: data generation, dataset construction, model training, and performance evaluation
- HEP ML Lab, developed in Python 3.9, involves an end-to-end complete process

- Also works on previously generated files from MadGraph (root format)
- Observable naming convention that directly links physical objects with type of observable, similar to Python syntax (case insensitive, aliases)
- For objects that don't exist it returns a list of length zero instead of an error, automatically judged as False when applying cuts

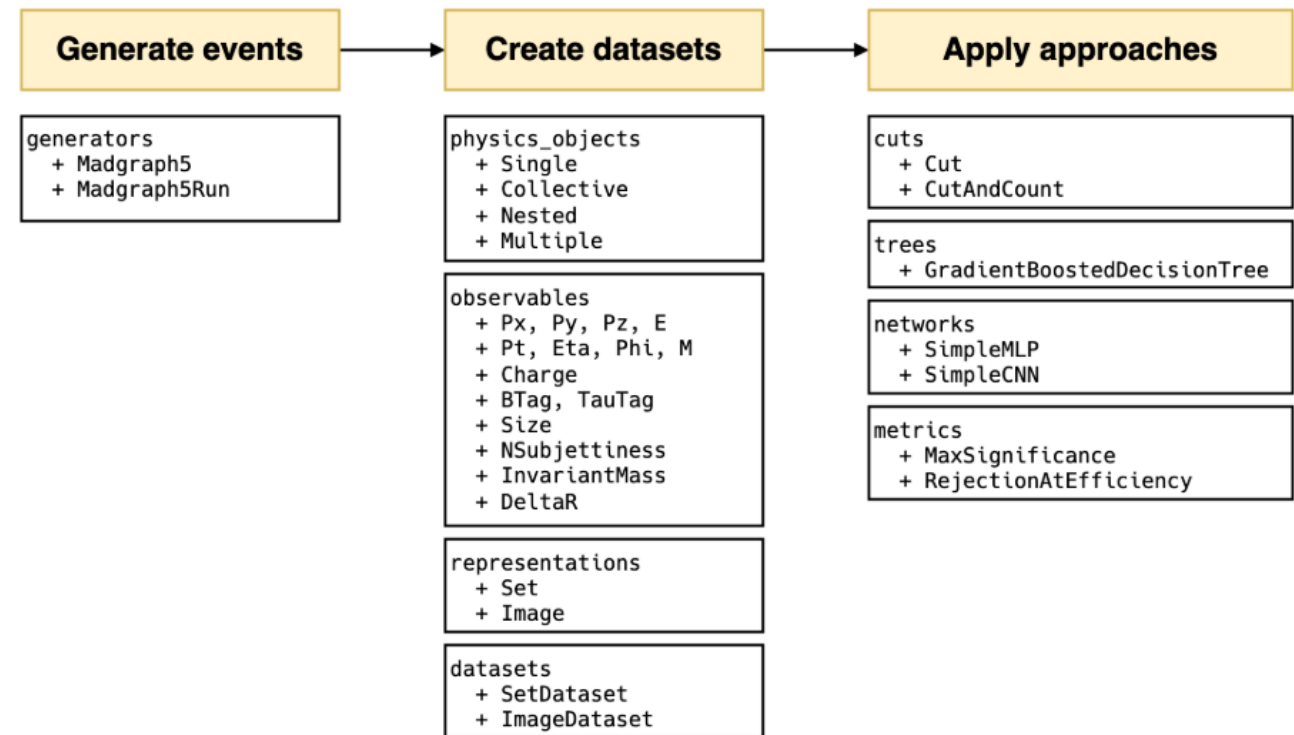


Figure 1: All modules in the hml framework and main classes in each module.

HEP ML Lab: An end-to-end framework for applying machine learning into phenomenology studies – Jing Li, Hao Sun [arXiv:2405.02888 \[hep-ph\]](https://arxiv.org/abs/2405.02888)

- Keras style interface design for approaches module
- Available cut-and-count (with automatical cut optimization on multiple variables), decision trees and neural network that interfaces with current frameworks
- Only two basic deep learning models at the moment but will add more in the future
- Can apply different approaches and later see which one is the best
- Assessment of training with significance $\sigma = \frac{S}{\sqrt{S+B}}$ and background rejection at a fixed signal significance $= 1/\epsilon_b$

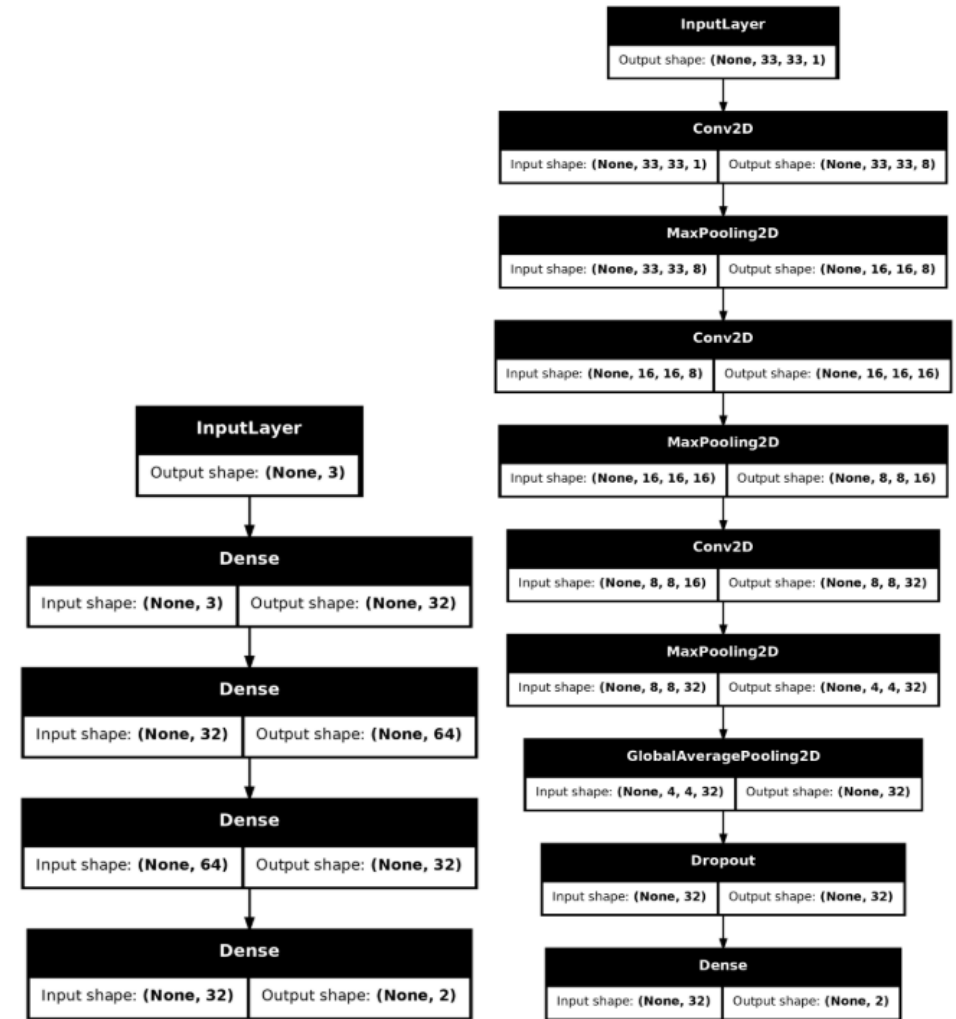


Figure 4: The structure of the SimpleMLP and SimpleCNN models.