Probing BSM effects in $e^+e^- \to WW$ with machine learning

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Current work with Lingfeng Li and Jiayin Gu

- How to probe beyond the standard model physics?
- Why do we study the process of diboson?
- Why it is necessary to use Machine Learning Method?

Big Picture

- Build large colliders $\rightarrow$ high energy $\rightarrow$ discover new particles!

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- No guaranteed discovery!

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  $\searrow$

  do precision measurements $\rightarrow$ discover new physics indirectly!

- Build a larger collider?
- No guaranteed discovery!

- Higgs Factory! (CEPC,ILC,etc)
- Standard Model Effective Field Theory(SMEFT)

The Standard Model Effective Field Theory

- $[\mathcal{L}_{SM}] \leq 4$. Why?
  - Renormalizable
  - Higher dimensional operators are fine as long as we are happy with finite precision in perturbative calculation.
- Assuming Baryon and Lepton numbers are conserved,

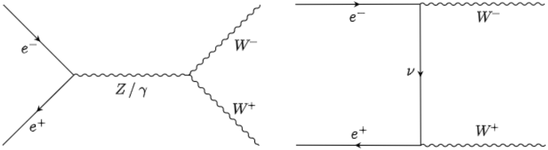
$$\mathcal{L}_{SMEFT} = \mathcal{L}_{SM} + \sum_i \frac{\mathrm{c}_\mathrm{i}^{(6)}}{\Lambda^2} \mathcal{O}_i^{(6)} + \sum_j \frac{\mathrm{c}_\mathrm{j}^{(8)}}{\Lambda^4} \mathcal{O}_j^{(8)} + \cdots$$

- If $\Lambda \gg E, v$,then SM + dimension-6 operators are sufficient to parameterize the physics around the electroweak scale.

Why Diboson

- Diboson is an important part of the precision measurement program
- Connected to the higgs couplings in the SMEFT frame
- Can be measured very well at Higgs factories

EFT Parameterization

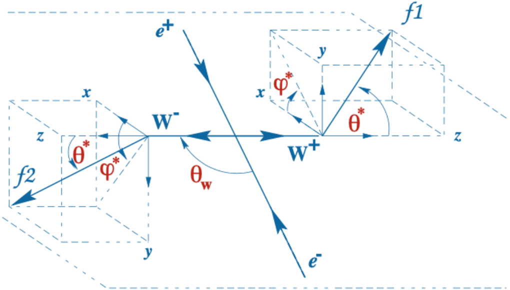


- Focusing on tree-level CP-even dimension-6 contributions
- $e^-e^+ \to WW$ can be parameterized by

$$\delta g_{1,Z},\ \delta\kappa_\gamma,\ \lambda_Z,\ \delta g^{ee}_{Z,L},\ \delta g^{ee}_{Z,R},\ \delta g^{e\nu}_{W},\ \delta m_W$$

- m_W is better constrained, so we can simply set $\delta m_W = 0$

$e^- e^+ \to WW$ with Histogram



- The TGCs are sensitive to the differential distributions
  - One could do a fit to the binned distributions of all angles.
  - Not the most efficient way of extracting information.
  - Correlations among angles are sometimes ignored.

$e^-e^+ \to WW$ with Optimal Observable

- What are Optimal Observables?

  Diehl, M., Nachtmann, O., 1994. Zeitschrift Für Physik C Part Fields 62, 397–411.

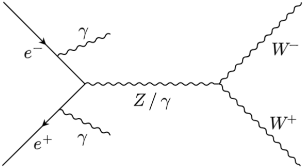
  - In the limit of large statistics (everything is Gaussian) and small parameters (linear contribution dominates), the best possible reaches can be derived analytically!

    $$\frac{d\sigma}{d\Omega} = S_0 + \Sigma_i S_{1,i} g_i, \qquad c_{ij}^{-1} = \int d\Omega \frac{S_{1,i} S_{1,j}}{S_0} \cdot \mathcal{L}$$

- The optimal observable is a function of 5 angles and is given by $\mathcal{O}_i = \frac{S_{1,i}}{S_0}$

Systematic Effects

- Initial state radiation



- Jet smearing
- Detect effects
  - final state jets can not be distinguished
  - neutrino cannot be directly measured
- They are systematic effects

Systematic Effects

- In simulation, systematic effects can't be ignored

Systematic Effects

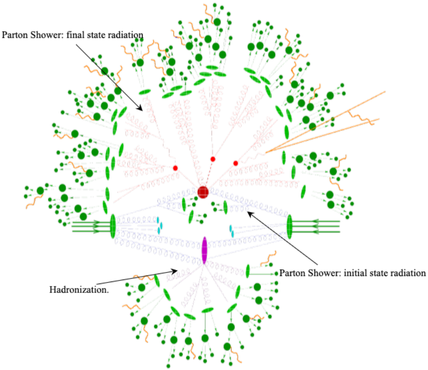
- In simulation, systematic effects can't be ignored
- Analytical methods become more difficult and time consuming when we include more realistic effects.
- Naively applying optimal observables could lead to a bias

Likelihood Inference

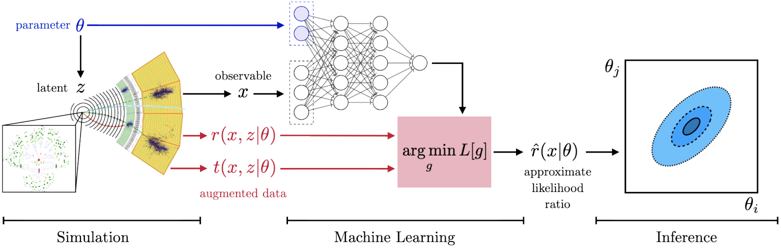
- Neyman-Pearson lemma says the best statistics to test new physics is the likelihood ratio given data x and theory parameters θ_1 and θ_0

$$r(x|\theta_0, \theta_1) = \frac{p(x|\theta_0)}{p(x|\theta_1)}$$

- The key thing is $r(x|\theta_0, \theta_1)$
- Analytical methods always computational consuming and ignore systematic effects



Likelihood Inference



- Johann Brehmer, etc develop new simulation-based inference techniques that are tailored to the structure of particle physics processes.[arXiv:1805.00013]Brehmer, J, Cranmer, K, Louppe, G, Pavez, J
- Machine Learning method can extract more information from x to predict the likelihood ratio

Particle-Physics Structure

- The likelihood function can be written as

$$p(x|\theta) = \int dz \ p(x, z|\theta) = \int dz \ p(x|z)p(z|\theta)$$

- Here $p(z|\theta) = 1/\sigma(\theta) d\sigma/dz$ is the parton level density distribution.
- $p(x|z)$ describes the probabilistic evolution from the parton-level four-momenta to observable particle properties

$$p(x|z) = \int dz_d \int dz_s \int dz \ p(x|z_d)p(z_d|z_s)p(z_s|z)$$

Particle Structure

- We can extract more information from the simulator by defining joint likelihood ratio and joint score

$$r(x, z|\theta_0, \theta_1) = \frac{p(x|z)p(z|\theta_0)}{p(x|z)p(z|\theta_1)} = \frac{p(z|\theta_0)}{p(z|\theta_1)}$$

$$\alpha(x, z|\theta_0, \theta_1) = \nabla_{\theta_0} r(x, z|\theta_0, \theta_1)|_{\theta_0=\theta_1}$$

- The loss function is

$$\mathcal{L}[\hat{g}(x)] = \int dxdz\ p(x, z|\theta)|g(x, z) - \hat{g}(x)|^2$$

- The loss function is minimized when $g(x, z) = \hat{g}(x)$

ML Algorithm: ALICE

- Approximate likelihood with improved crossentropy estimator
- Directly predict the likelihood ratio
- Loss function $\mathcal{L}$ is

$$\mathcal{L}(\hat{s}) \propto \sum_{x} [s(x, z|\theta_0, \theta_1) \log(\hat{s}(x)) + (1 - s(x, z|\theta_0, \theta_1)) \log(1 - \hat{s}(x))]$$

- Here $s(x, z|\theta_0, \theta_1) = \frac{1}{1+r(x,z|\theta_0,\theta_1)}$
- $\hat{r}(x|\theta_0, \theta_1)$ can be reconstructed by $\hat{s}(x) = \frac{1}{1+\hat{r}(x|\theta_0,\theta_1)}$

ML Algorithm: SALLY

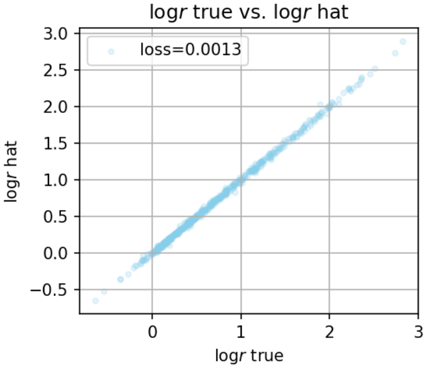
- Score approximates likelihood locally
- likelihood ratio can also be parameterized by Wilson coefficients

$$\hat{r}(x, \theta) = 1 + \sum_i \hat{\alpha}_i(x)\theta_i$$

- And we can predict α_i term as well
- Loss function $\mathcal{L}$ is

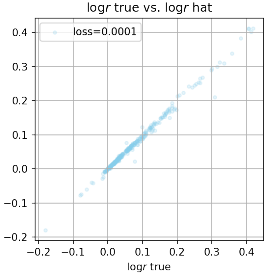
$$\mathcal{L} \propto \sum_i |\hat{\alpha}_i(x) - \alpha_i(x, z|\theta_0, \theta_1)|^2$$

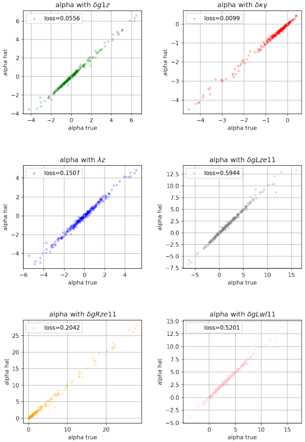
Prediction of Likelihood Ratio:ALICE



- ALICE method offers a precise way to predict the likelihood ratio directly.

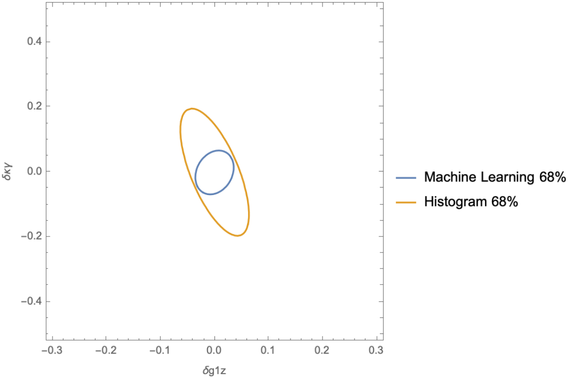
Prediction of Likelihood Ratio:SALLY





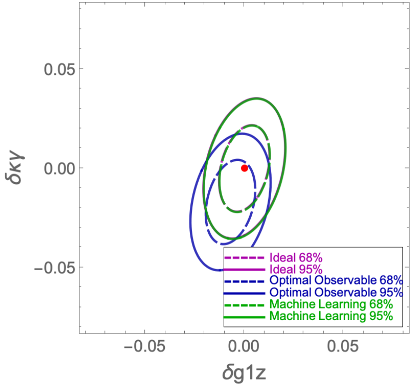
- We can construct the $\hat{r}(x, \theta)$ by predicting the alpha term and give an analytical expression of $\hat{r}(x, \theta)$

Estimation of the Boundary:Compared with Histogram



- no bias
- precise bounds along individual directions
- weak constraints in other directions

Estimation of the Boundary:Compared with OO



- Once you get the $\hat{r}(x|\theta)$, $\chi^2 = -2\sum_i \log(\hat{r}(x_i|\theta))$
- The χ^2 analysis shows that ML method can correct the large bias and give a strong constrain on the model parameters.

Conclusion

- Future colliders will generate large amount of data, ML will benefit it a lot
- By machine learning, we can construct 6D likelihood ratio to improve the global fit result
- Machine Learning can easily take care of systematic effects as long as the MC simulation is accurate.
- Machine learning is (likely to be) the future

Thanks!

Backup Slides: $e^-e^+ \to WW$ parameterization

$$
\begin{aligned}
\mathcal{L}_{TGC} = & \, igs_{\theta_w} A^\mu (W^{-\nu} W^+_{\mu\nu} - W^{+\nu}_{\mu\nu}) \\
& + ig(1+\delta g_1^Z) c_{\theta_w} Z^\mu (W^{-\nu} W^+_{\mu\nu} - W^{+\nu}_{\mu\nu}) \\
& + ig[(1+\delta\kappa_Z) c_{\theta_w} Z^{\mu\nu} + (1+\delta\kappa_\gamma) s_{\theta_w} A^{\mu\nu}] W^-_\mu W^+_\nu \\
& + \frac{ig}{m_W^2} (\lambda_Z c_{\theta_w} Z^{\mu\nu} + \lambda_\gamma s_{\theta_w} A^{\mu\nu} W^{-\rho}_\nu W^+_{\rho\mu})
\end{aligned}
$$

- Imposing Gauge invariance one obtains $\delta\kappa_Z = \delta g_{1,Z} - t^2_{\theta_w} \delta\kappa_\gamma$ and $\lambda_Z = \lambda_\gamma$
- $\delta g_{1,Z}, \; \delta\kappa_\gamma, \; \lambda_Z, \; \delta g^{ee}_{Z,L}, \; \delta g^{ee}_{Z,R}, \; \delta g^{e\nu}_W, \; \delta m_W$