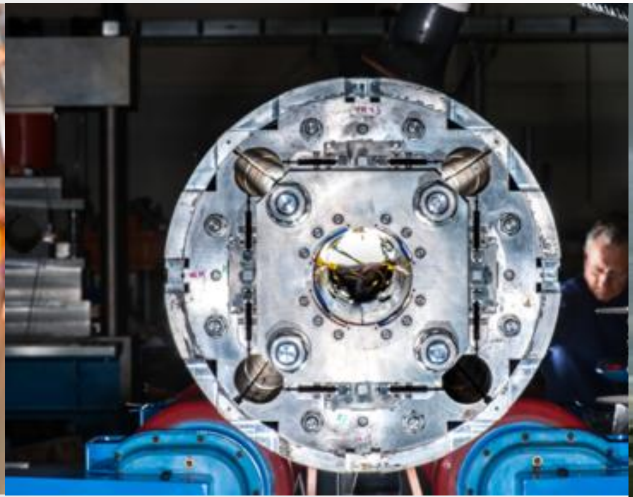
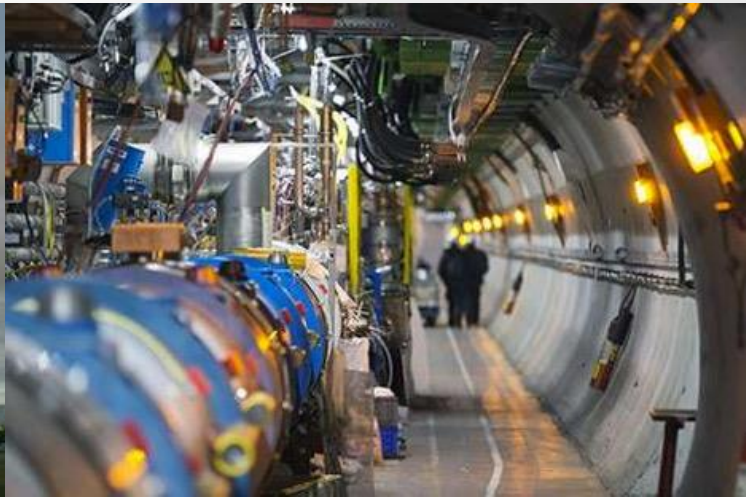
(SOME MORE) MACHINE LEARNING APPLICATIONS FOR SMEFT

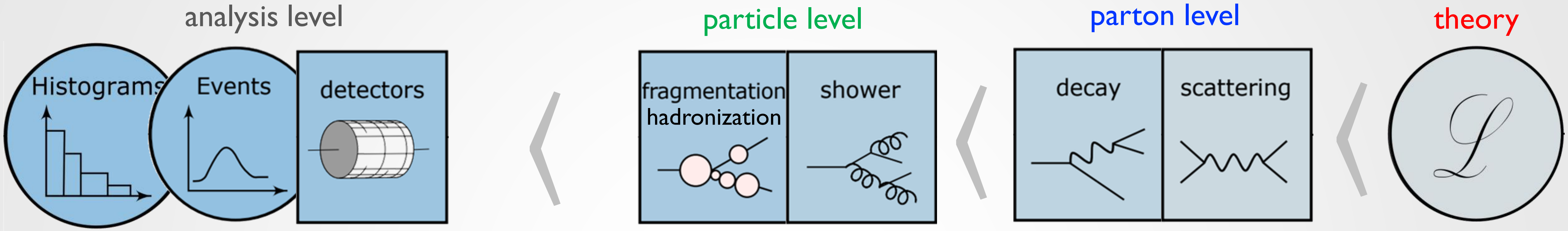
R. Schöfbeck (HEPHY Vienna), Feb. 29th, 2024, COMETA general meeting



A CONDITIONAL SEQUENCE

adapted from arXiv:2211.01421



$$p(x_{\rm det}|\theta) = \int dz_{\rm ptl} \int dz_{\rm p} [\cdots]\ p(x_{\rm det}|z_{\rm ptl}) \qquad p(z_{\rm ptl}|z_{\rm p}) \qquad p(z_{\rm p}|\theta)$$

Likelihood ratio is the optimal statistic (Neyman-Pearson Lemma)

$$\mathrm{LR}(x_{\rm det}|\mathrm{H}_1, \mathrm{H}_2) \equiv \frac{p(x_{\rm det}|\theta = \mathrm{H}_1)}{p(x_{\rm det}|\theta = \mathrm{H}_2)}$$

1. This is a ratio of integrals; z is integrated.
2. Would like to evaluate for varying **θ**, **ν**

1. Generators run in 'forward mode'
2. Pick up uncertainties
   $p(z_{\rm ptl}|z_{\rm p}, \nu_{\rm th.})$
   $p(x_{\rm det}|z_{\rm ptl}, \nu_{\rm exp.})$

$$\frac{1}{\sigma_\theta}\frac{d\sigma_\theta}{dz_p} = p(z_{\rm p}|\theta)$$

parton-level differential cross section ~ pdf

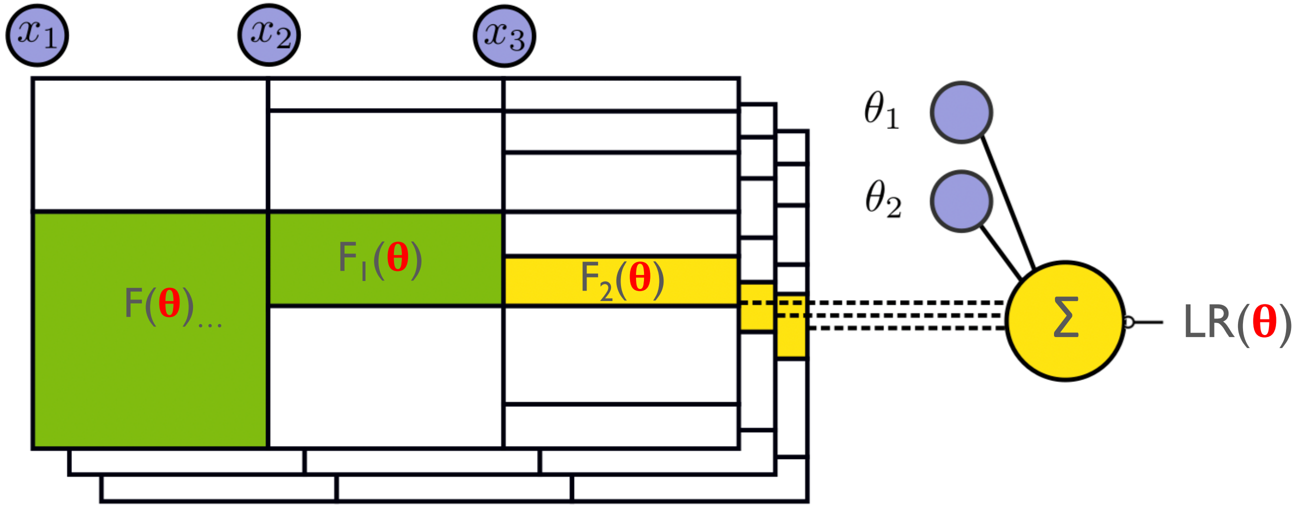
~~$p(\theta)$~~

θ NOT stochastic; Frequentist

THE TOPICS IN THIS TALK

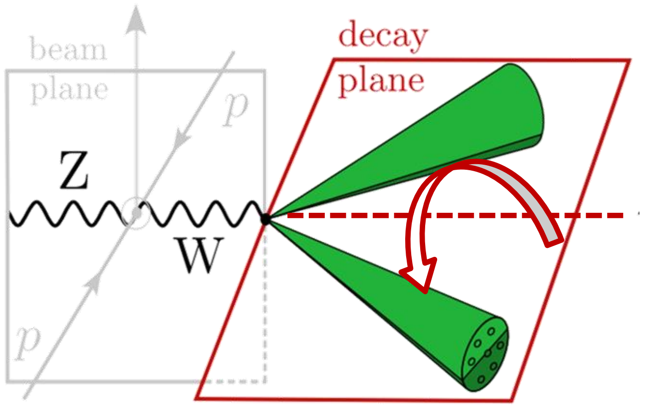
1. How can we learn the SMEFT likelihood ratio with trees

   "Simulation based inference" in WH and ZH final states



[arXiv:2107.10859, arXiv:2205:12976]

2. Obtain SMEFT constraints from particles in boosted fat jets with equivariant gNNs in semi-leptonic WZ final states



[arXiv: 2401.10323]

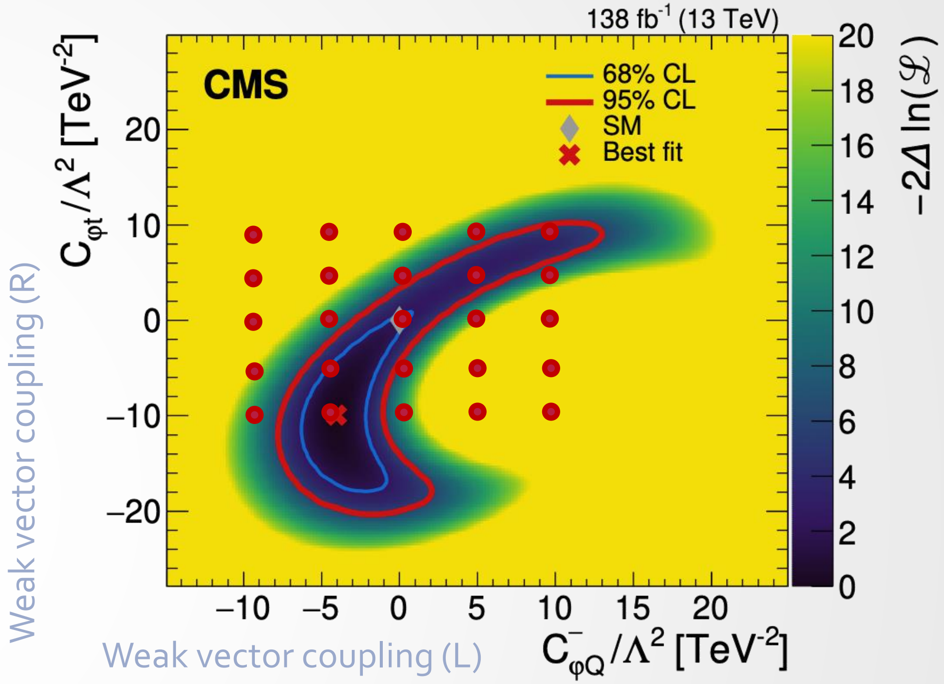
CAN WE JUST LEARN EFT EFFECTS "ON AVERAGE"?

$$L = \sum_{\boldsymbol{\theta} \in \mathcal{B}} \int \mathrm{d}\boldsymbol{x} \, \left(p(\boldsymbol{x}|\boldsymbol{\theta}) \hat{f}(\boldsymbol{x})^2 + p(\boldsymbol{x}|\mathrm{SM})(1 - \hat{f}(\boldsymbol{x}))^2 \right)$$

$\boldsymbol{\theta}$ - ignorant

mixing signals &
case dependent mixes

$$f^*(\boldsymbol{x}) = \frac{1}{1 + r_{\mathcal{B}}(\boldsymbol{x})} \qquad r_{\mathcal{B}}(\boldsymbol{x}) = \frac{\frac{1}{|\mathcal{B}|} \sum_{\boldsymbol{\theta} \in \mathcal{B}} p(\boldsymbol{x}|\boldsymbol{\theta})}{p(\boldsymbol{x}|\mathrm{SM})}$$



[TOP-21-001]

- We can try to learn EFT effects on average with this "likelihood ratio trick"
- Sending 'mixed signals' to the loss function
  - Averages the training data set - suboptimal when linear effects dominate
  - Classifier does not reflect knowledge on the $\boldsymbol{\theta}$-dependence
- Back to the drawing board & inject $\boldsymbol{\theta}$ polynomial SMEFT dependence in estimator.

EXPLOITING SMEFT REWEIGHTING

$$L = \sum_{\theta\in\mathcal{B}} \left(\langle \hat{f}(x;\theta)^2 \rangle_\theta + \langle (1-\hat{f}(x;\theta))^2 \rangle_{\text{SM}} \right)$$

θ - aware — *EFT sample* — *SM sample*

We start with SM and BSM samples

$$= \sum_{\theta\in\mathcal{B}} \int \mathrm{d}x\,\mathrm{d}z \left(p(x,z|\theta)\hat{f}(x;\theta)^2 + p(x,z|\text{SM})(1-\hat{f}(x;\theta))^2 \right)$$

Let's write this under one integral
z … latent space

SM sample

$$= \sum_{\theta\in\mathcal{B}} \int \mathrm{d}x\,\mathrm{d}z\, p(x,z|\text{SM}) \left(r(x,z|\theta)\hat{f}(x;\theta)^2 + (1-\hat{f}(x;\theta))^2 \right)$$

"joint" likelihood ratio

… and use just one sample
& joint likelihood ratio

$$r = \frac{p(x_{\text{det}},\cdots,z_{\text{ptl}},\cdots,z_{\text{p}}|\theta)}{p(x_{\text{det}},\cdots,z_{\text{ptl}},\cdots,z_{\text{p}}|\text{SM})} = \frac{p(x_{\text{det}}|z_{\text{ptl}})\cdots p(z_{\text{ptl}}|z_{\text{p}})\cdots p(z_{\text{p}}|\theta)}{p(x_{\text{det}}|z_{\text{ptl}})\cdots p(z_{\text{ptl}}|z_{\text{p}})\cdots p(z_{\text{p}}|\text{SM})} = \frac{p(z_{\text{p}}|\theta)}{p(z_{\text{p}}|\text{SM})} \sim \frac{|\mathcal{M}(z_{\text{p}},\theta)|^2}{|\mathcal{M}(z_{\text{p}},\text{SM})|^2} = w_i(\boldsymbol{\theta})$$

Change in likelihood of simulated observation x with latent "history" z going from "SM" to **θ**

staged simulation in forward mode: Intractable factors cancel

re-calcuable theory prediction

weighted simulation

PARAMETRIZED CLASSIFIERS

K. Cranmer , J. Pavez , and G. Louppe [1506.02169]
J. Brehmer, K. Cranmer, G. Louppe, J. Pavez [1805.00013]
[1805.00020]
"Madminer" [1805.12244]
J. Brehmer, F. Kling, I. Espejo, K. Cranmer [1907.10621]

$$L = \sum_{\theta\in\mathcal{B}} \int \mathrm{d}x\,\mathrm{d}z\, p(x,z|\mathrm{SM}) \left(r(x,z|\theta)\hat{f}(x;\theta)^2 + (1-\hat{f}(x;\theta))^2 \right)$$

MSE or cross entropy

$$\hat{f}(x;\theta) = \frac{1}{1+\hat{R}(x;\theta)}$$

invert likelihood trick

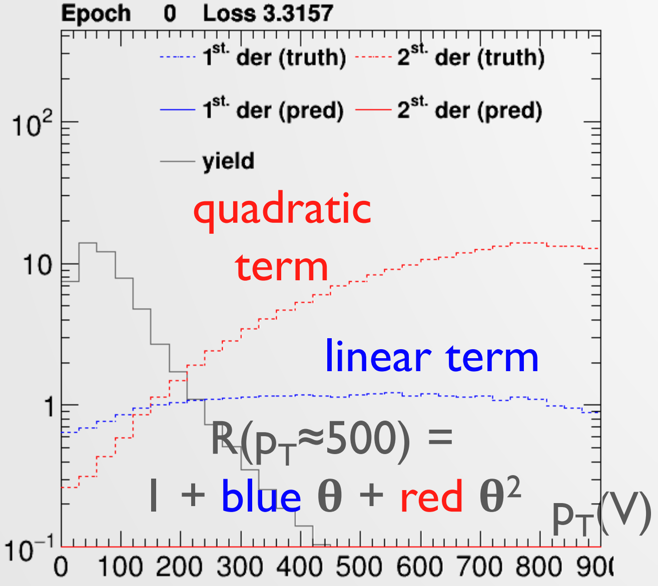
insert model knowledge: fit universal coefficient functions

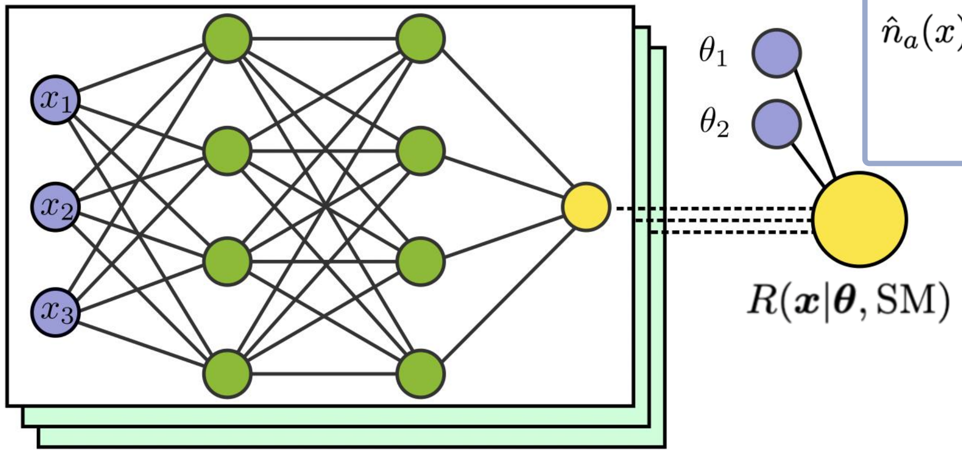
$$\hat{R}(x;\theta) = \left(1 + \sum_a \theta_a \hat{n}_a(x)\right)^2 + \sum_a \left(\sum_{b\geq a} \theta_b \hat{n}_{ab}(x)\right)^2$$

$$\hat{n}_a(x) \to \left.\frac{\partial_a p(x|\ \theta\ )}{p(x|\mathrm{SM})}\right|_{\theta=\mathrm{SM}} = \left.\frac{\partial_a \int \mathrm{d}z\ p(x,z|\theta)}{\int \mathrm{d}z\ p(x,z|\mathrm{SM})}\right|_{\theta=\mathrm{SM}}$$

Integrates latent space!

Similar to S. Chen, A. Glioti, G. Panico, A. Wulzer
JHEP 05 (2021) 247
arXiv:2308.05704



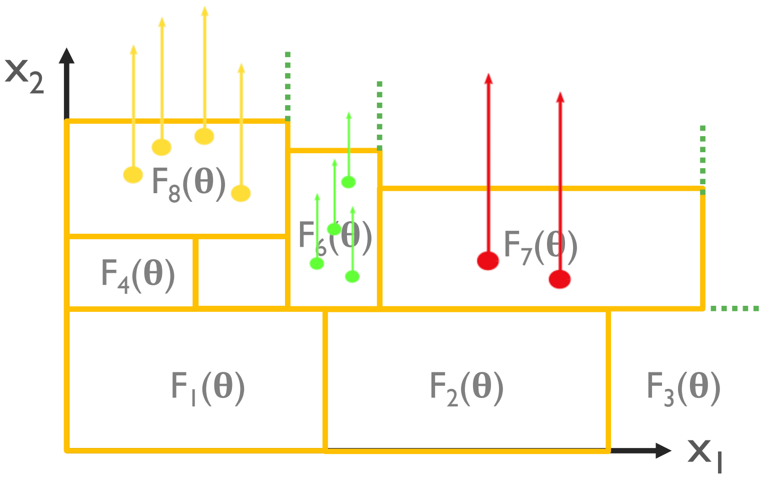


Why would you want to use trees instead?

A SIMPLE TREE ALGORITHM

[arXiv:2107.10859, arXiv:2205:12976]

Phase-space partitioning



A simple tree

index-function (non-linearity)

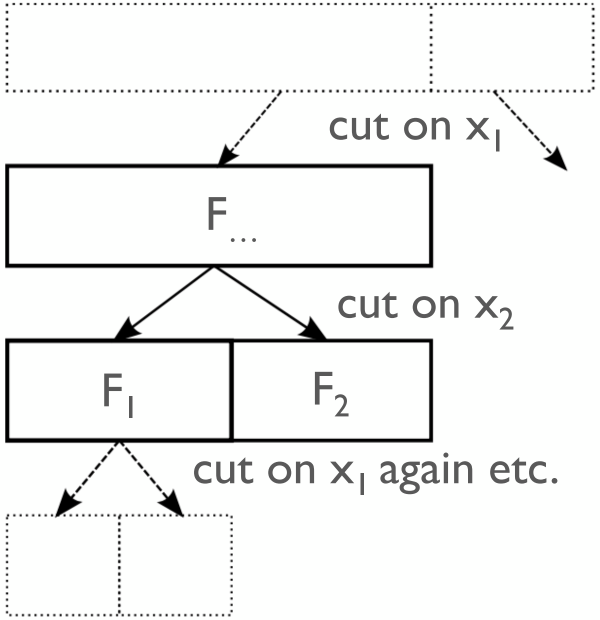
$$\hat{F}(\boldsymbol{x},\boldsymbol{\theta}) = \sum_{j\in\mathcal{J}} \mathbb{1}_j(\boldsymbol{x}) F_j(\boldsymbol{\theta})$$

phase space partitioning J

prediction F_j

need to solve for partitioning J and $\{F_j\}$

training phase:
e.g. "CART" algo



- A tree is a hierarchical phase-space partitioning ($\mathcal{J}$)
  - the novelty in the Boosted Information Tree is that we associate each region j with a polynomial $F_j(\boldsymbol{\theta})$
  - Note: A tree algorithm can have an arbitrarily complicated predictive function; here it is a SMEFT polynomial
- Fitting tree: Optimize "node split positions" on some loss. Trained (e.g. greedily) on the *ensemble*.

PARAMETRIC TREES FOR SMEFT

[arXiv:2107.10859, arXiv:2205:12976]

Want to regress in r, exploiting its the polynomial $\boldsymbol{\theta}$ dependence

$$r(x,z|\theta) = \frac{\mathrm{d}\sigma(\boldsymbol{x},\boldsymbol{\theta})/\mathrm{d}\boldsymbol{x}}{\mathrm{d}\sigma(\boldsymbol{x},\mathrm{SM})/\mathrm{d}\boldsymbol{x}}$$

→ will allow to compute the optimal LLR test statistic $q(\mathcal{D})$

$$L = \sum_{\boldsymbol{\theta}\in\mathcal{B}} \int \mathrm{d}\boldsymbol{x}\,\mathrm{d}\boldsymbol{z}\, p(\boldsymbol{x},\boldsymbol{z}|\mathrm{SM}) \left(r(x,z|\theta) - \hat{F}(\boldsymbol{x},\boldsymbol{\theta})\right)^2$$

Tree ansatz

$$\hat{F}(\boldsymbol{x},\boldsymbol{\theta}) = \sum_{j\in\mathcal{J}} \mathbb{1}_j(\boldsymbol{x}) F_j(\boldsymbol{\theta})$$

find optimal partitioning | find optimal predictor

$F_j(\boldsymbol{\theta})$ polynomial with const. coeff. (per node)

Eliminate the predictive function

$$F_j(\boldsymbol{\theta}) = \frac{\sum_{i\in j} w_i(\boldsymbol{\theta})}{\sum_{i\in j} w_i(\boldsymbol{\theta}_0)} = \frac{\int \mathrm{d}z \frac{\mathrm{d}\sigma_{\boldsymbol{\theta}}}{\mathrm{d}(x,z)}}{\int \mathrm{d}z \frac{\mathrm{d}\sigma_{\mathrm{SM}}}{\mathrm{d}(x,z)}}$$

NP!

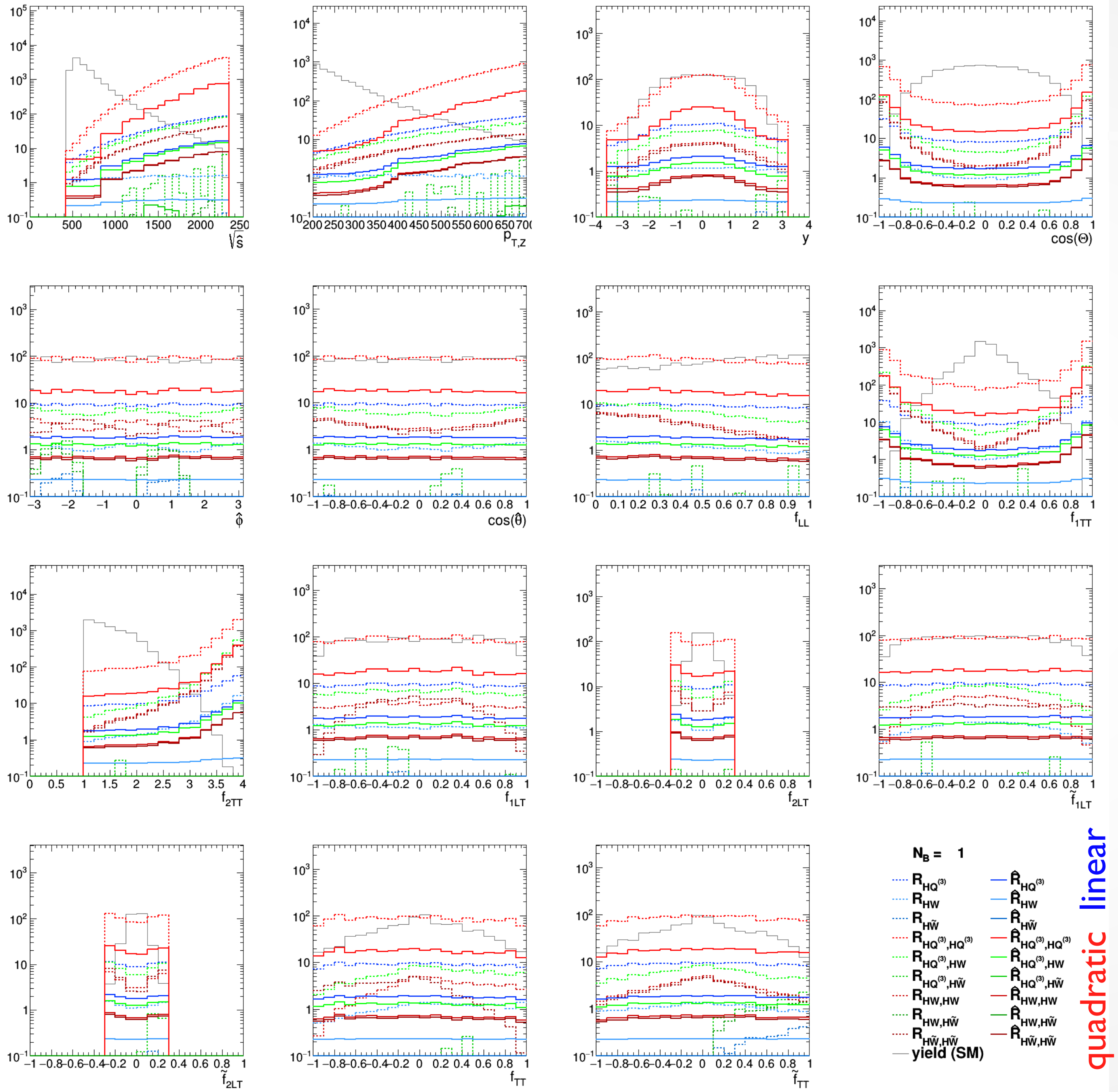
The latent space integration happens at the node-level and removes learnable parameters

Solve for optimal partitioning with greedy CART algorithm

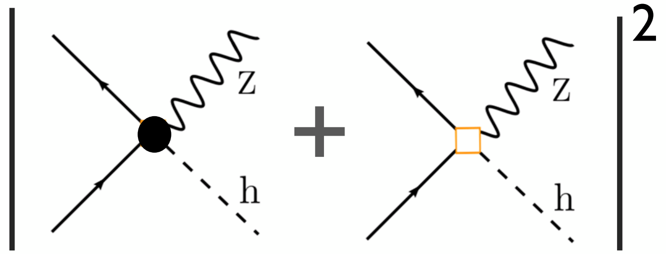
$$L = -\sum_{\boldsymbol{\theta}\in\mathcal{B}} \sum_{j\in\mathcal{J}} \frac{w_j^2(\boldsymbol{\theta})}{w_j(\boldsymbol{\theta}_0)} = -\sum_{j\in\mathcal{J}} \sum_{\boldsymbol{\theta}\in\mathcal{B}} \theta^a\theta^b I_{ab}^{(j)} + \mathcal{O}(\boldsymbol{\theta}-\boldsymbol{\theta}_0)^3$$

We're optimizing the Fisher information!

We'll find an optimized tree.
→ boost



- Realistic case: model of the ZH process
- "Boosted Information Tree (BIT)"
  - 3 WC, 9 DOF, 500k events, ZH
  - 200 trees, D=5, 9 minutes of training
  - also more realistic study, including backgrounds [2107.10859], [2205.12976]
- Learning coefficient functions to compute parametrized optimal oberables

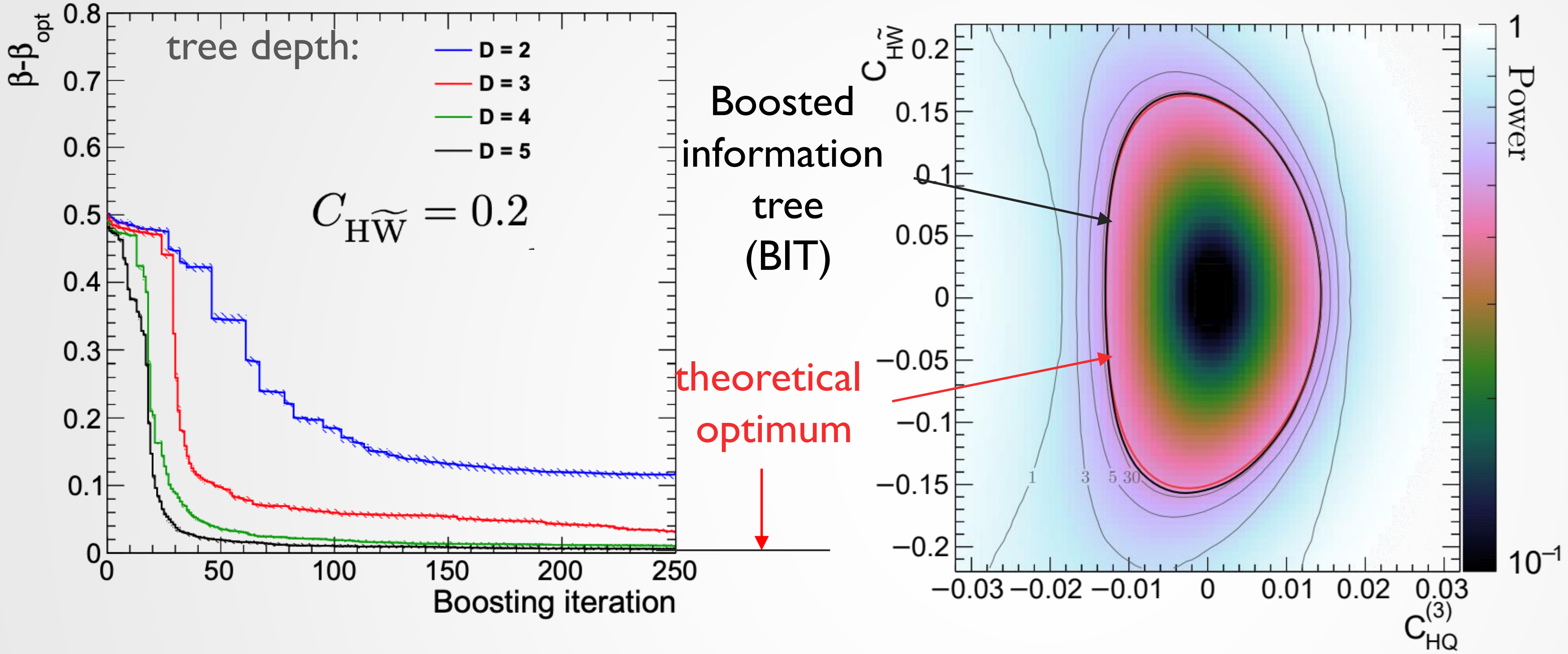


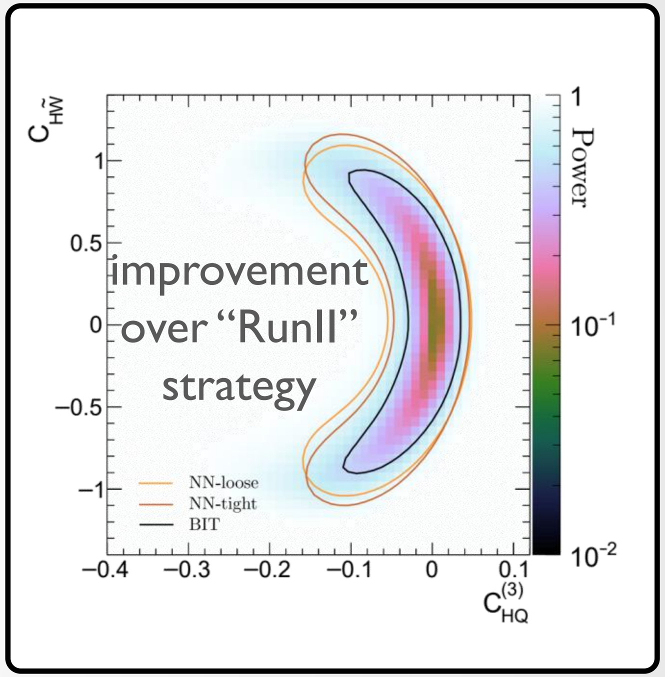
$$= \sigma^{\rm SM} + \frac{\theta}{\Lambda^2}\sigma^{\rm int} + \frac{\theta^2}{\Lambda^4}\sigma^{\rm quad}$$

→ parametrized LR(θ)

OPTIMALITY IN TEST CASES

[arXiv:2107.10859, arXiv:2205:12976]

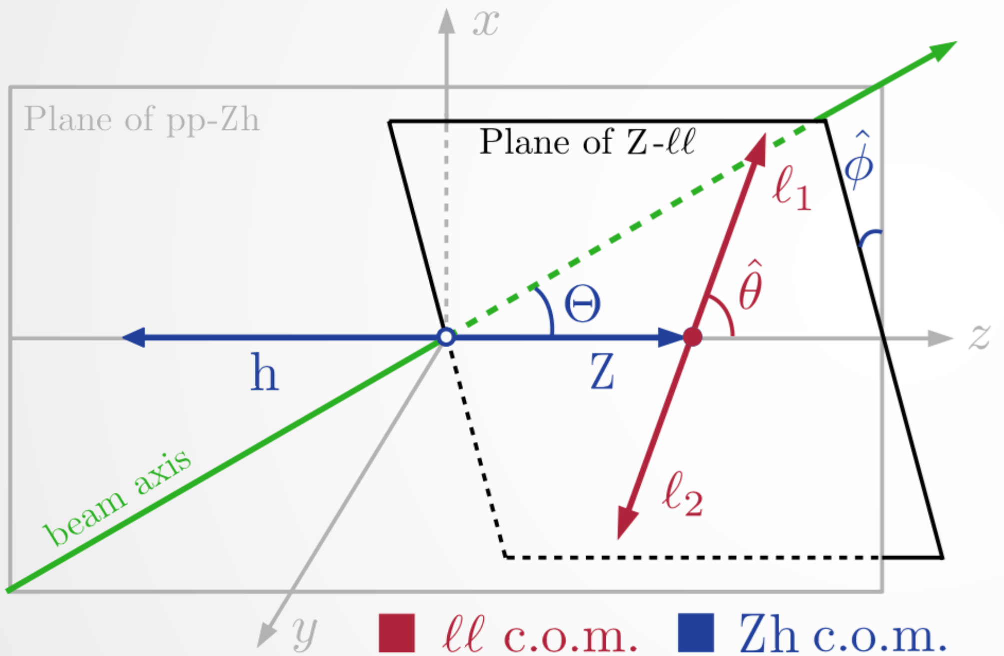




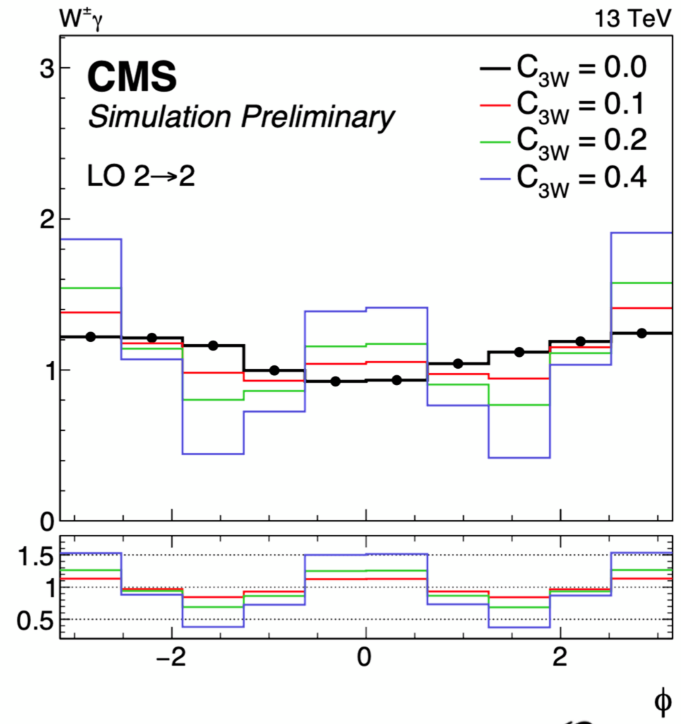
- Obtain parametrized classifiers with 20-40% improvements for two-at-a-time limits
- No free lunch – Analysis dependent choices are needed
  - Systematics treatment for unbinned analyses (beyond Higgs $M_{4\ell}$) less far developed
- Is it all worth it in higher dimensions? Yes! [ML4EFT] shows factor ~5 improvements in marginalized limits

SMEFT SENSITIVITY OF DIBOSON FINAL STATES

- SMEFT sensitivity in diboson derives from "resurrected" interference
  PLB 20 (2018) 776, JHEP 06 (2021) 031
  - Reconstruction of production- & decay planes boost sensitivity up to x10



CMS Wγ analysis PRD 105(222)052003

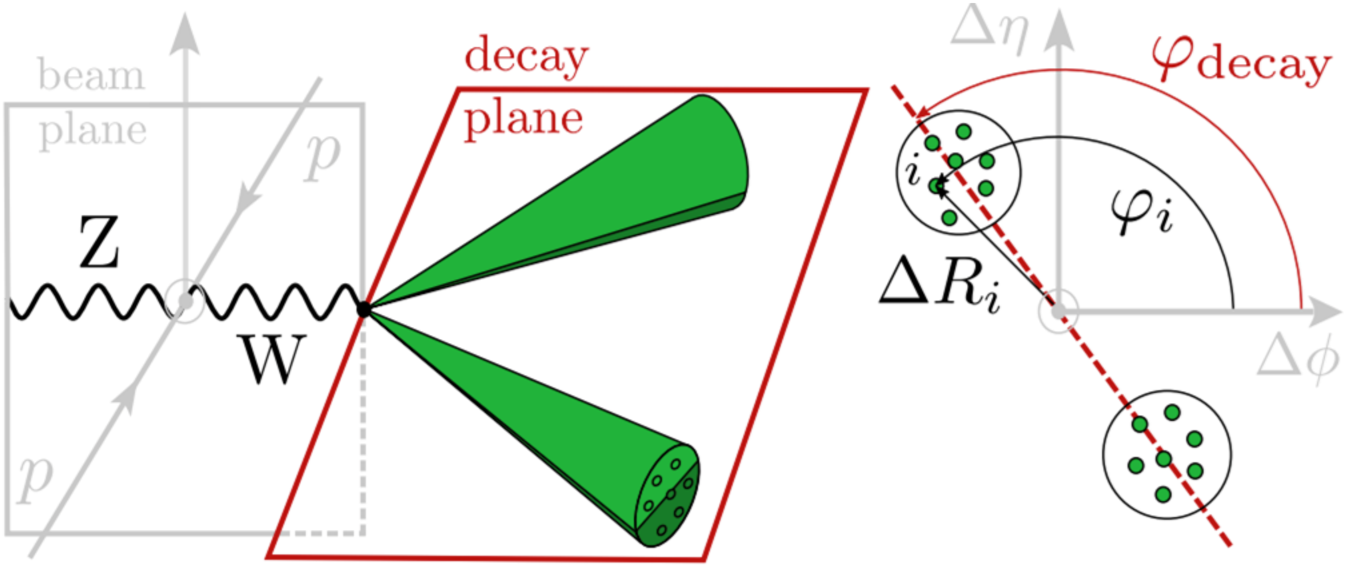


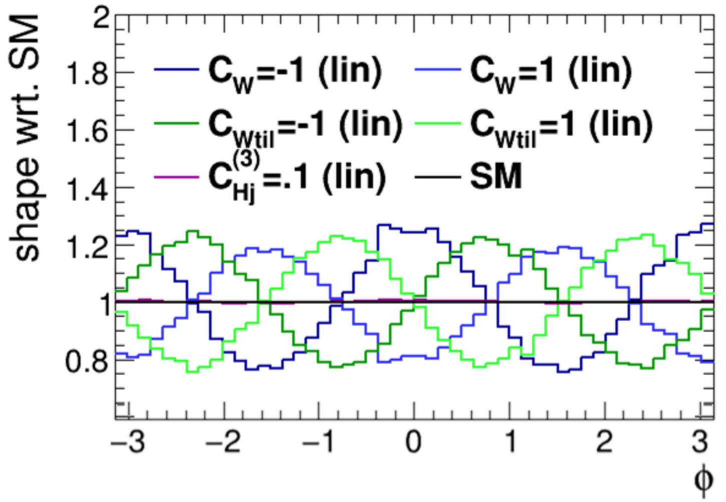
CP-even: $\cos(2\phi) \leftrightarrow \mathcal{O}_W$

CP-odd : $\sin(2\phi) \leftrightarrow \mathcal{O}_{\widetilde{W}}$

- Are all angles equal? No;
  - The leading linear cW/cWtil sensitivity comes from ϕ.
  - Can we exploit this fact in semi-leptonic final states of pp→WZ?

PP ⟶ W(BOOSTED) Z(⟶ℓℓ)

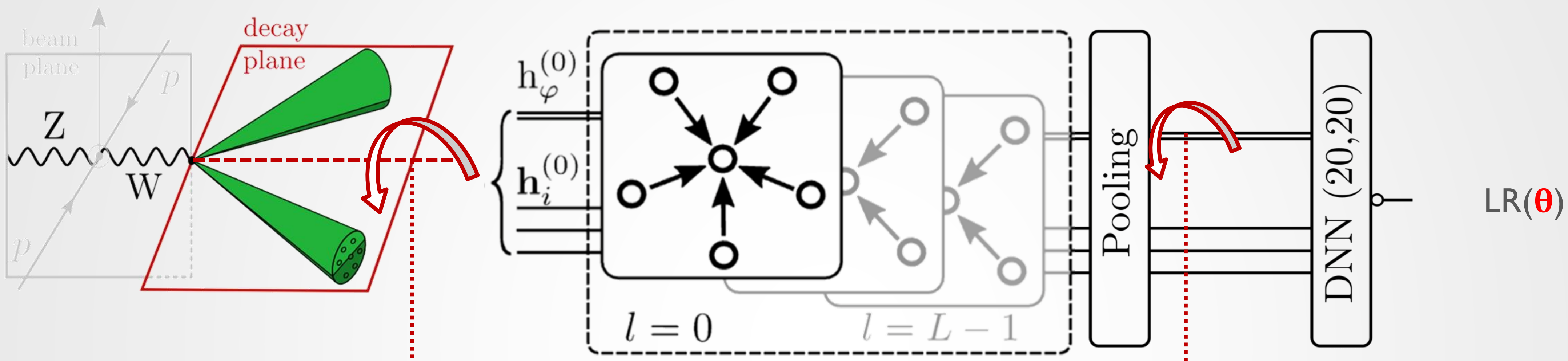




- Measure particles in the WZ frame with respect to the beam plane
- The linear SMEFT effect in WZ is in the tilt of the decay plane vs. production plane.

NETWORK ARCHITECTURE

[arXiv: 2401.10323]



Input data

$$\mathrm{h}_{\varphi,i}^{(0)} = \varphi_i, \quad \mathbf{h}_i^{(0)} = \Delta R_i$$

and $p_{T,i}$

SO(2)- Equivariance

$$\mathbf{h}_i^{(l+1)} = \sum_{j\in N(i)} \omega_j^{(N(i))} \boldsymbol{f}_{\mathrm{h}}^{(l)} \left(\mathbf{h}_i^{(l)}, \mathbf{h}_j^{(l)}, h_{\varphi,i}^{(l)} - h_{\varphi,j}^{(l)}\right)$$

$$e^{ih_{\varphi,i}^{(l+1)}} = e^{ih_{\varphi,i}^{(l)} + i\sum_{j\in N(i)} \omega_j^{(N(i))} f_{\Phi}^{(l)}\left(\mathbf{h}_i^{(l)}, \mathbf{h}_j^{(l)}, h_{\varphi,i}^{(l)} - h_{\varphi,j}^{(l)}\right)}$$

Loss function

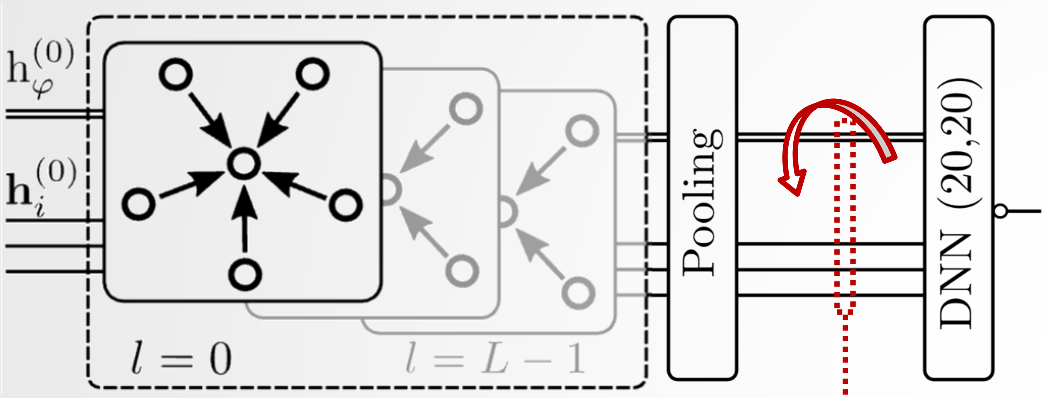
$$L = \sum \omega_j(\mathrm{SM}) \left(\mathbf{t}(\mathbf{x}_j, \mathbf{z}_j) - \hat{\boldsymbol{f}}(\mathbf{x}_j)\right)^2$$

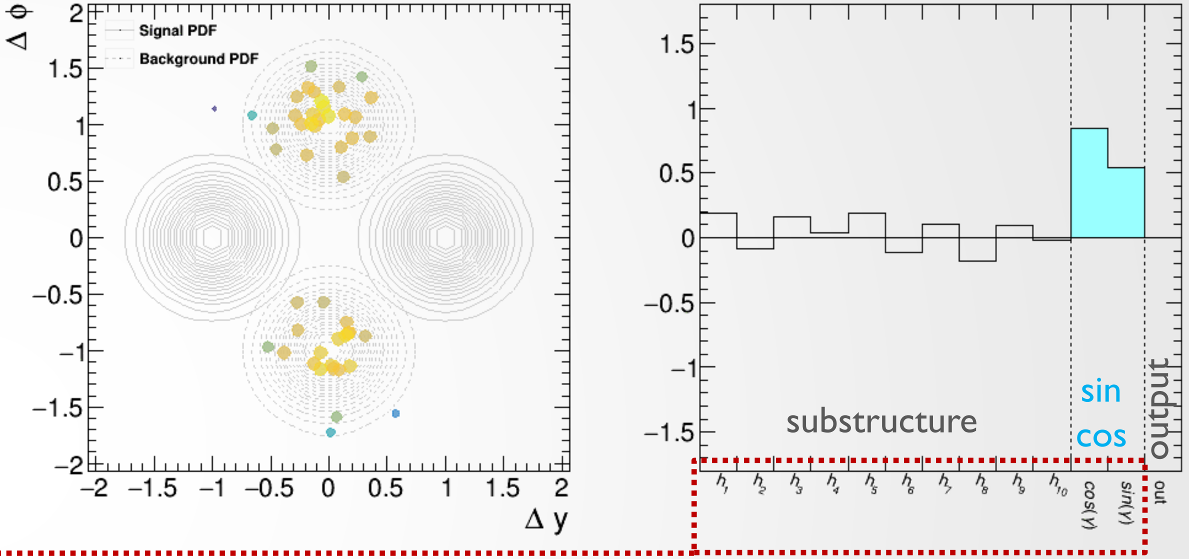
- Particles are measured in the production plane; fed into gNN and try to learn the linear SMEFT term.
- gNN efficiently encodes the jet's substructure. But the linear SMEFT will be in the substructure's spatial orientation.
  - Include a special network feature that *transforms under rotations around the jet axis exactly like the input*: Equivariance.
  - Rotating the input particles by an angle of ΔΦ results transforms the output by exp(i ΔΦ); feed into readout DNN.

WHAT DOES THE GNN LEARN?

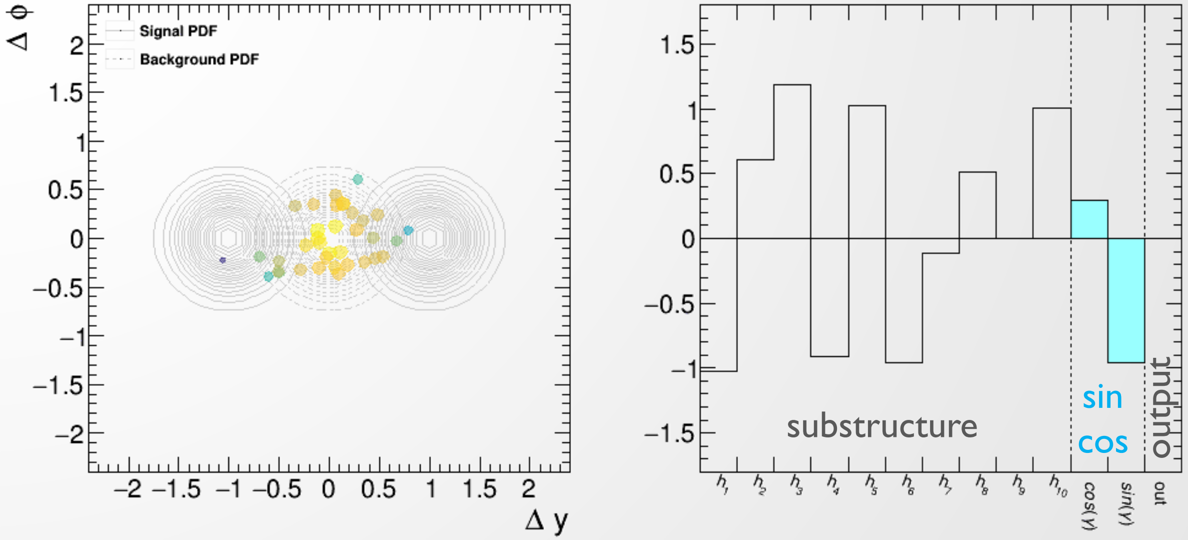
[arXiv: 2401.10323]

- Toy studies! Let's look at the internal representation.





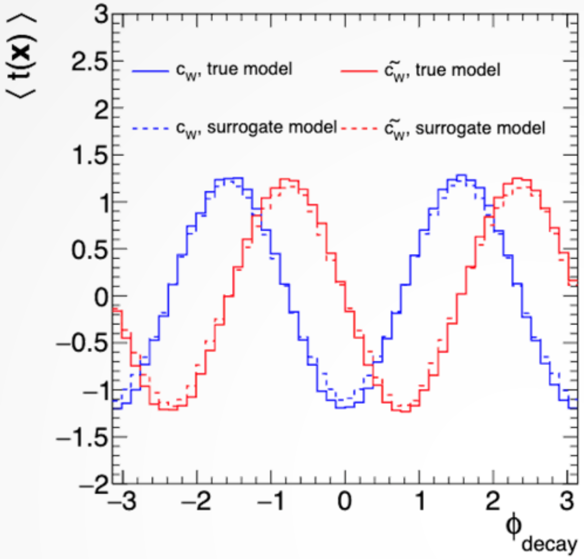
- Top: Classify different 2-prong orientations
  - The information is ONLY in the rotational angle
  - The internal scalars are irrelevant
- Bottom: 2-prong vs one- prong *classification*
  - The discriminative information is in the substructure
  - The rotational angle is not important



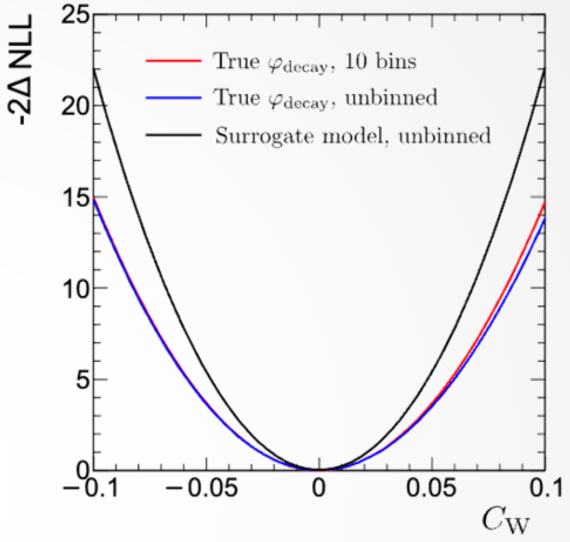
FIRST RESULTS

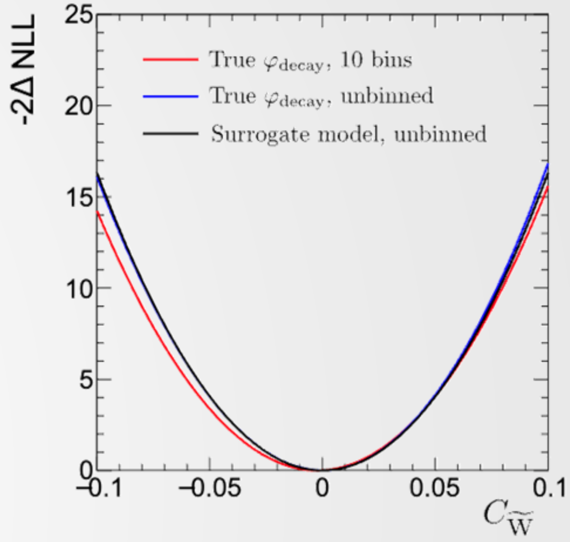
[arXiv: 2401.10323]

- Learned linear SMEFT sensitivity (Score) vs. true decay plane angle



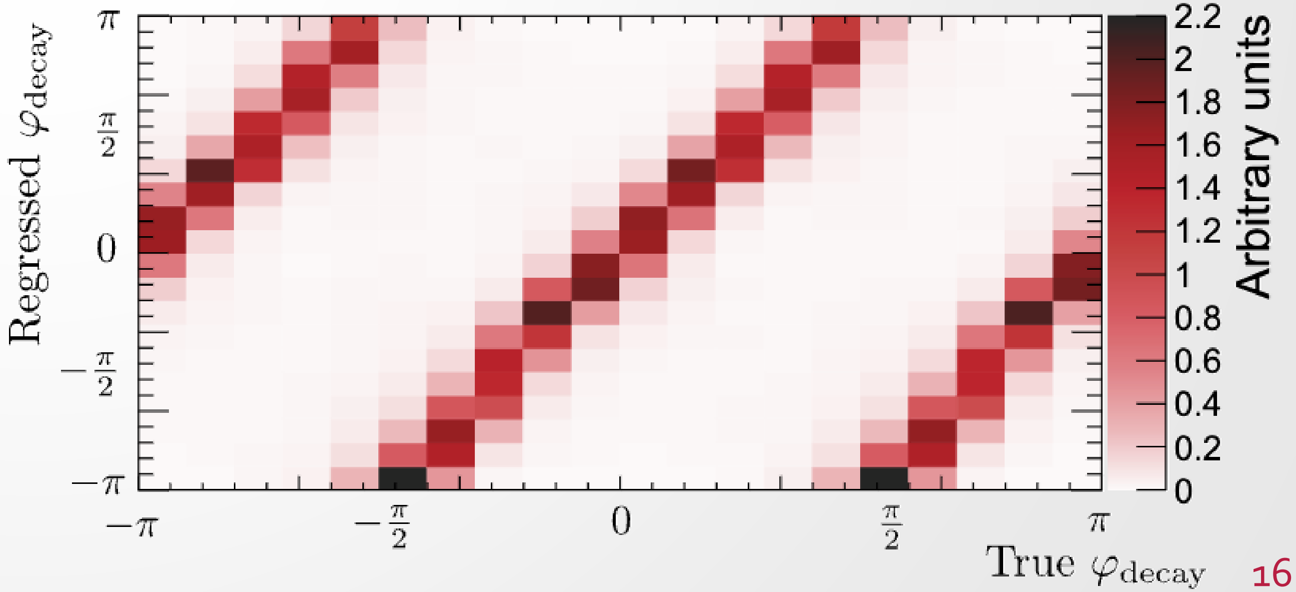
- Delphes mock-up limits





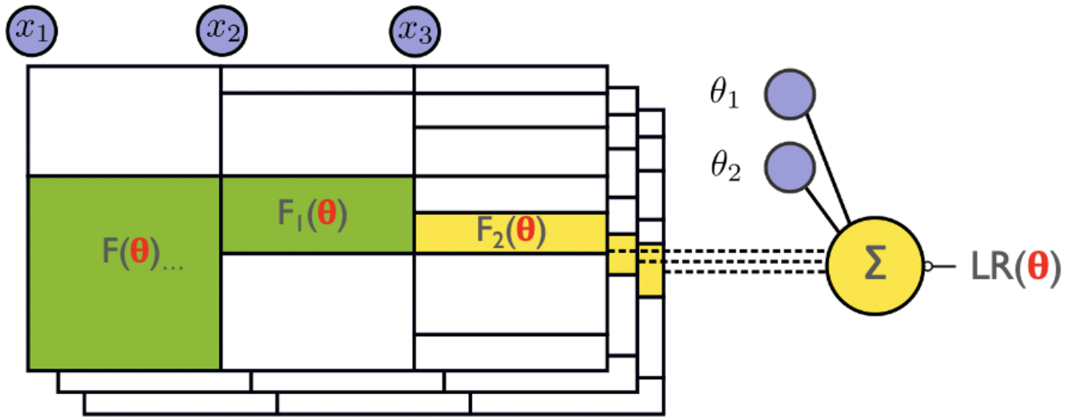
- Bottom: angular regression in ϕ

- Example of a refined inductive bias to leverage new(-ish) ML developments for SMEFT



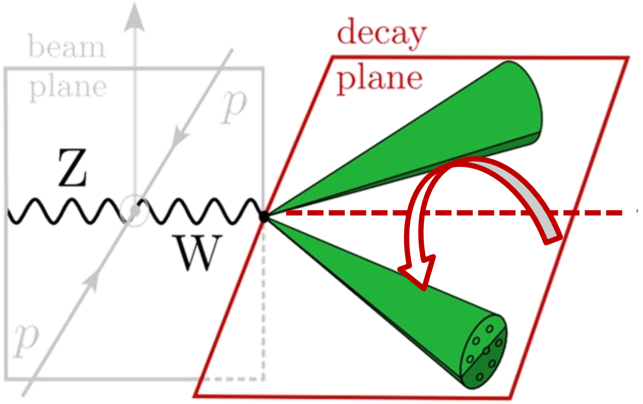
SUMMARY

1. Trees are efficient & useful for learning high-dimensional SMEFT dependence



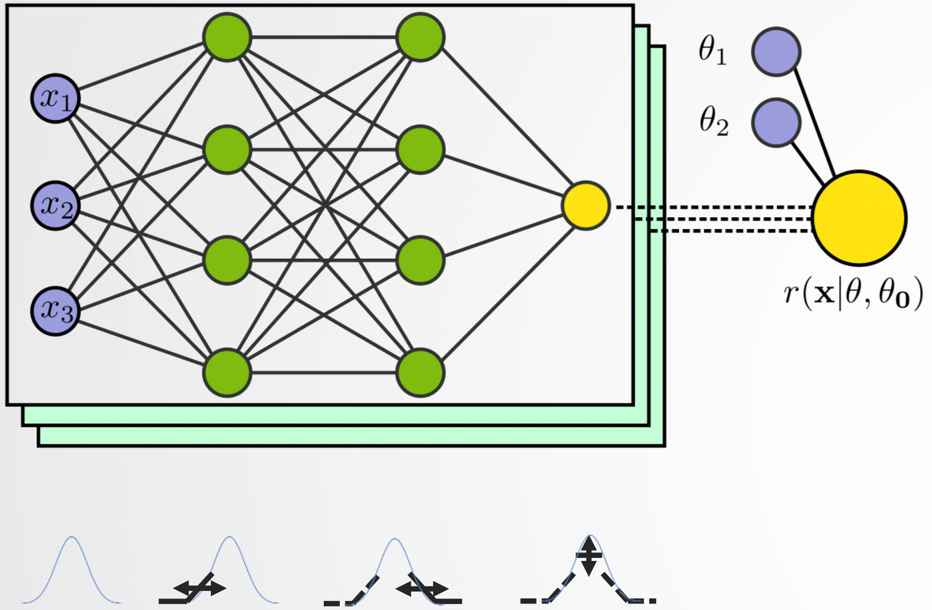
[arXiv:2107.10859, arXiv:2205:12976]

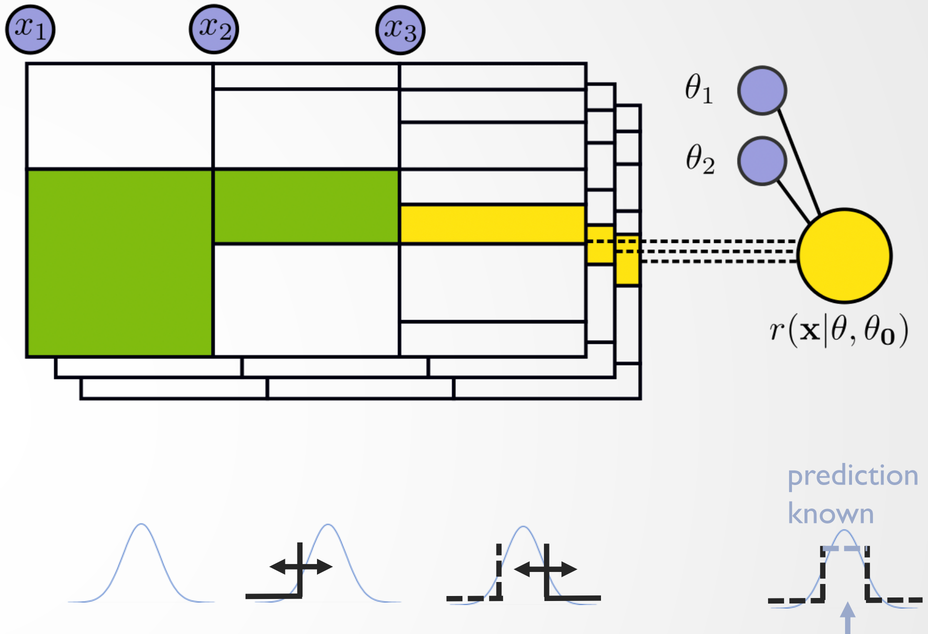
2. Equivariant gNNs give access to the linear SMEFT term in hadronic final states



[arXiv: 2401.10323]

NETWORKS VS. TREES – WHAT IS THE BIG DEAL?





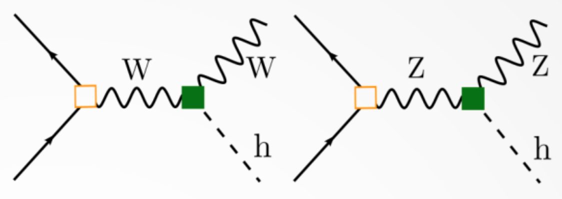
$$F_j(\boldsymbol{\theta}) = \frac{\sum_{i\in j} w_i(\boldsymbol{\theta})}{\sum_{i\in j} w_i(\boldsymbol{\theta}_0)} = \frac{\int \mathrm{d}z \frac{\mathrm{d}\sigma_{\boldsymbol{\theta}}}{\mathrm{d}(x,z)}}{\int \mathrm{d}z \frac{\mathrm{d}\sigma_{\mathrm{SM}}}{\mathrm{d}(x,z)}}$$

- Given a phase space region with EFT dependence: NN must select & predict
- In the Boosted Information Tree, the weak learner only selects
  - The prediction (F_j) is computed from the boxed events → integrates latent space
  - The regression problem is solved with computational complexity of classification
    - Speed advantage at high operator dimensions!

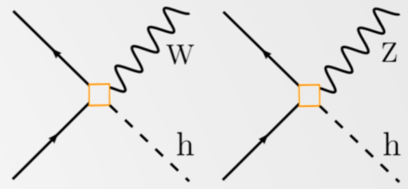
GOALS FOR MACHINE-LEARNING *OF* EFT

[EPJC 81 (2021) 178]

- SMEFT effects can be
  1. in the tails of the distributions because, e.g. 4-point functions grow with energy
  2. in angular observables & correlations, sometimes encoding CP-violating effects
     - "interference resurrection" PLB 2017 11 086
       "method of moments" JHEP 06 (2021) 031
     - Enhance / single out the linear term
       - Up to triple-angular correlations, x5-10 boost in sensitivity
  3. on top of "kinematically complex" backgrounds
     - Def: Usually amenable to classification MVAs
     - Unify the training target with classification



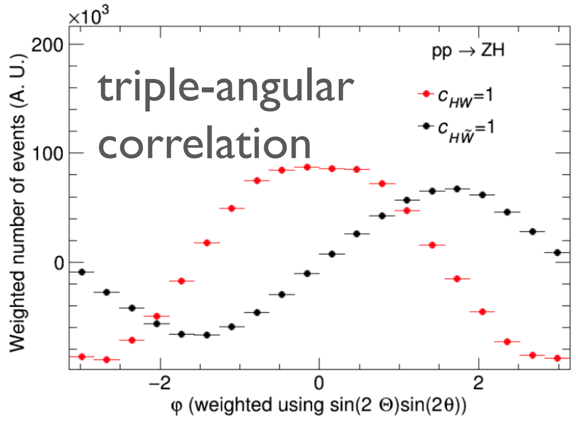
cHW/cHWtil

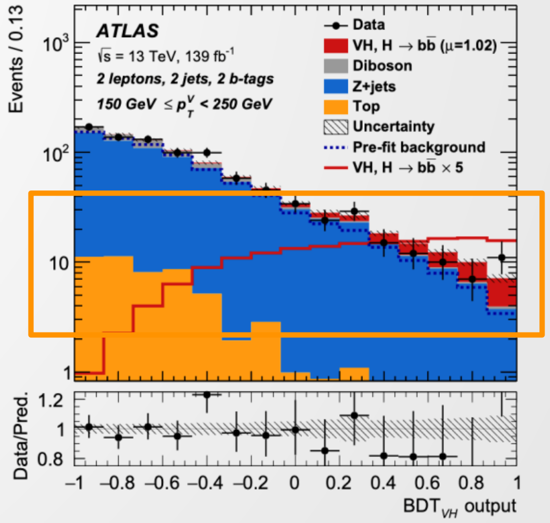


cHQ3 ↔ also in ttZ

Tree-level SMEFT amplitude of ZH (transverse polarisation):

$$\hat{\mathcal{M}}_\sigma^{\lambda=\pm} = g_Z m_Z \sqrt{\hat s}\left[\frac{g_{Z\sigma}}{\hat s - m_Z^2} + c_{\theta_W}\left(1+\frac{\hat s - m_h^2}{m_Z^2}\right)\left(\frac{g_{Z\sigma}c_{\theta_W}}{\hat s - m_Z^2}+\frac{Q_q e s_{\theta_W}}{\hat s}\right)\frac{v^2}{\Lambda^2}C_{HW} - \frac{2i\lambda k\sqrt{\hat s}}{m_Z^2}c_{\theta_W}\left(\frac{g_{Z\sigma}c_{\theta_W}}{\hat s - m_Z^2}+\frac{Q_q e s_{\theta_W}}{\hat s}\right)\frac{v^2}{\Lambda^2}C_{H\widetilde{W}}\right] + g_Z^2\frac{\sqrt{\hat s}}{m_Z}T_q^{(3)}\frac{v^2}{\Lambda^2}C_{HQ^{(3)}},$$





HOW TO PARAMETRIZE?

- Quantum field theory: Differential cross section predict polynomial SM-EFT dependence:

$$d\sigma(\boldsymbol{\theta}) \propto |\mathcal{M}_{\text{SM}}(\boldsymbol{z}) + \boldsymbol{\theta}_a \mathcal{M}^a_{\text{BSM}}(\boldsymbol{z})|^2 d\boldsymbol{z}$$

probability = wave function, squared

  - additivity of the matrix element → incur a simple (polynomial) dependence in **θ** for fixed configuration z

$$\frac{d\sigma(\boldsymbol{x},\boldsymbol{\theta})}{d\boldsymbol{x}} = \frac{d\sigma_{\text{SM}}(\boldsymbol{x})}{d\boldsymbol{x}} + \sum_a \theta_a \frac{d\sigma^a_{\text{int.}}(\boldsymbol{x})}{d\boldsymbol{x}} + \frac{1}{2}\sum_{a,b}\theta_a\theta_b \frac{d\sigma^{ab}_{\text{BSM}}(\boldsymbol{x})}{d\boldsymbol{x}}$$

- Neyman-Pearson: $q(\mathcal{D}) = \frac{L(\mathcal{D}|\boldsymbol{\theta}\quad)}{L(\mathcal{D}|\text{SM})}$ where $L(\mathcal{D}|\boldsymbol{\theta}) = \text{P}_{\mathcal{L}\sigma(\boldsymbol{\theta})}(N) \times \prod_{i=1}^{N} p(\boldsymbol{x}_i|\boldsymbol{\theta})$

"normalization" "shape"

$$q_{\boldsymbol{\theta}}(\mathcal{D}) = \underbrace{\mathcal{L}(\sigma_{\boldsymbol{\theta}} - \sigma_{\text{SM}})}_{\text{const.}} - \sum_{\boldsymbol{x}_i \in \mathcal{D}} \log R(\boldsymbol{x}_i|\boldsymbol{\theta},\text{SM})$$

Optimality can be achieved with cross-section ratio R or its **universal** coefficient functions R_a, R_{ab}

$$R(\boldsymbol{x}|\boldsymbol{\theta},\text{SM}) = \frac{d\sigma(\boldsymbol{x},\boldsymbol{\theta})/d\boldsymbol{x}}{d\sigma(\boldsymbol{x},\text{SM})/d\boldsymbol{x}} = 1 + \sum_a \theta_a R_a(\boldsymbol{x}) + \frac{1}{2}\sum_{a,b}\theta_a\theta_b R_{ab}(\boldsymbol{x})$$

$$\widehat{=} \left(1 + \sum_a \theta_a \hat{n}_a(\boldsymbol{x})\right)^2 + \sum_a \left(\sum_{b\geq a} \theta_b \hat{n}_{ab}(\boldsymbol{x})\right)^2$$

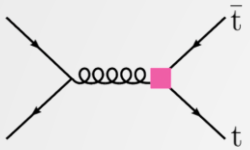
NB #1 Curse of dimensionality is lifted!!
15 operators → 136 coefficients

NB #2: R is positive: Fit universal dependence using the most general quadratic polynomial

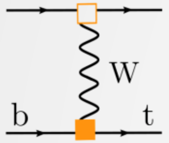
TOP QUARK PAIR + Z BOSON

JHEP 12 (2021) 083

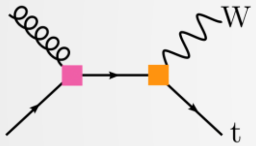
tt
811 pb



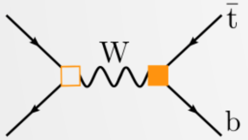
t (t-channel)
217 pb



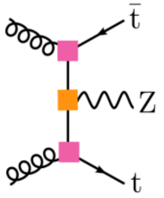
tW
72 pb



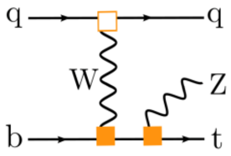
t (s-channel)
10 pb



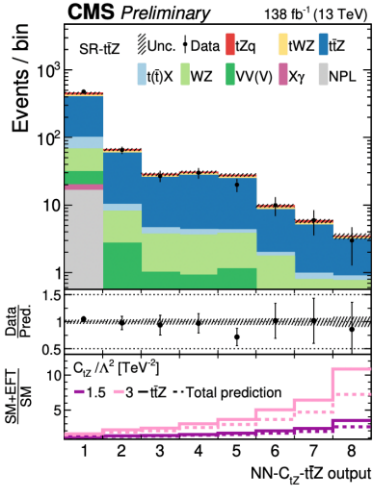
ttZ
1 pb

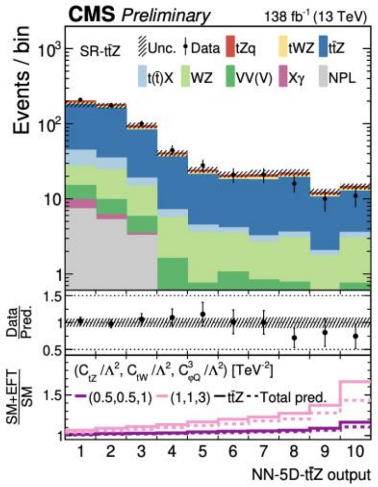


tZq
0.088 pb

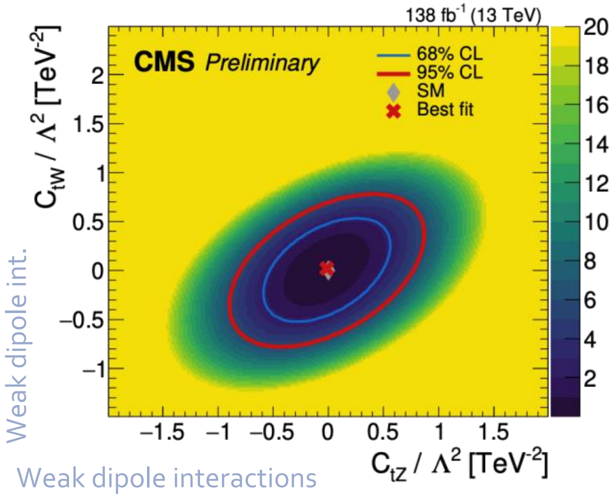


- Measure the top quark – Z boson coupling
- Train separate "SM vs. EFT" classifiers
  - Single operator O_{tZ}, O_{tW}, $O^3_{\phi Q}$
  - different trainings for different limits (!)
  - "likelihood trick" for SMEFT effects
- signal extraction with 1D, 2D, and 5D LL fit
  - Sampling of parameter space in the training
  - Targeted signals differ kinematically, but no parametrized training is used
  - Signal mix
  - no large linear terms → OK
- Best current limits



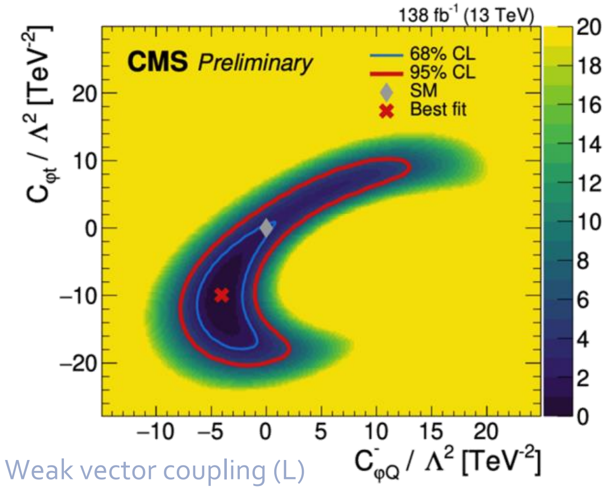


Weak dipole int.



Weak dipole interactions

Weak vector coupling (R)

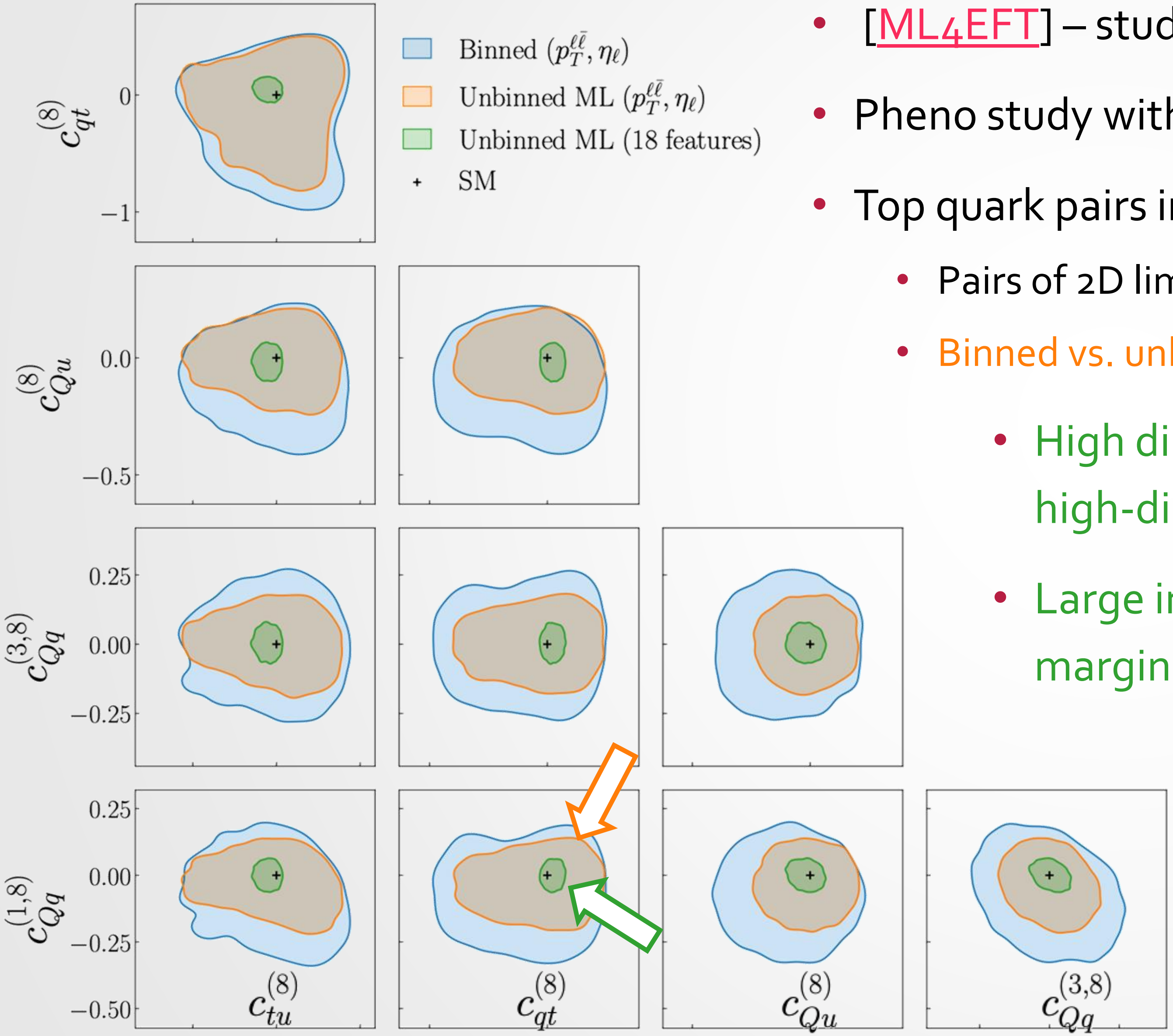


Weak vector coupling (L)

ML4EFT R. Ambrosio, J. Hoeve, M. Madigan, J. Rojo, V. Sanz [2211.02058]

IMPROVING HIGH DIMENSIONAL LIMITS

[CMS-TOP-PAS-20-006]



- [ML4EFT] – study ZH and top quark pairs
- Pheno study with parametrized NN classifiers
- Top quark pairs in low (N_f=2) and high feature dimension N_f=18
  - Pairs of 2D limits with 6 more ops marginalized
  - Binned vs. unbinned: Some gain w/ unbinned when using 2 features
    - High dimensional observation (N_f=18) constraining a high-dimensional (N_{coef}=8) model using an SM candle
    - Large improvement for N_f=18– mostly in the marginalized limits
- Take seriously constraining power from SM candle
- Whether the sensitivity gain survives systematics in an unbinned detector-level analysis is an open question

TOWARDS UNBINNED ANALYSIS

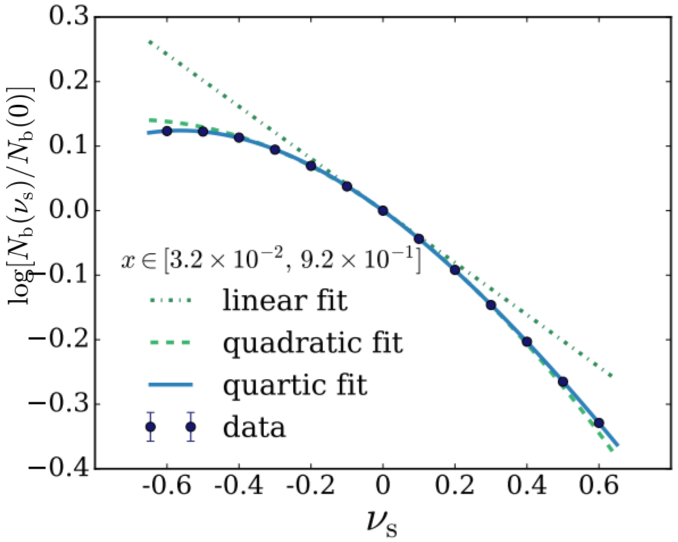
- Binned parametrized classifiers are impractical for high SMEFT parameter dimension
- What's missing to go all-in? Systematics.
  -
  -

$L = \sum$ ... $\theta,$

ematic ations cheap!

$\mathrm{M},\nu\!=\!0$

[Pierini et.al 2111.13633]

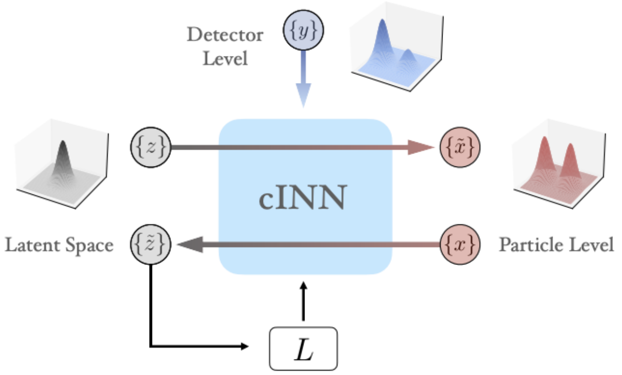


- A ch... h event counts in the profiling
- Divide & conquer #1: Experiments begun machine-learning certain nuisances: h_{damp}, b-fragmentation

- Divide & conquer #2: Unbinned unfolding for high dimensions
- Consider on the conditional pdf $p(x_{\mathrm{det}}|z_{\mathrm{ptl}})$ which can be evaluated in the forward mode
- Unfolding algorithms use Bayes' theorem

$$p(x_{\mathrm{det}}|z_{\mathrm{ptl}})p(z_{\mathrm{ptl}}) = p(z_{\mathrm{ptl}}|x_{\mathrm{det}})p(x_{\mathrm{det}})$$

  to learn $p(z_{\mathrm{ptl}}|x_{\mathrm{det}})$; GAN & other generative versions
  - Mostly iterative, to remove simulated prior



[community paper]
e.g. [OmniFold]
[cINN], [all]

- Report unbinned unfolded data; then SMEFT analysis

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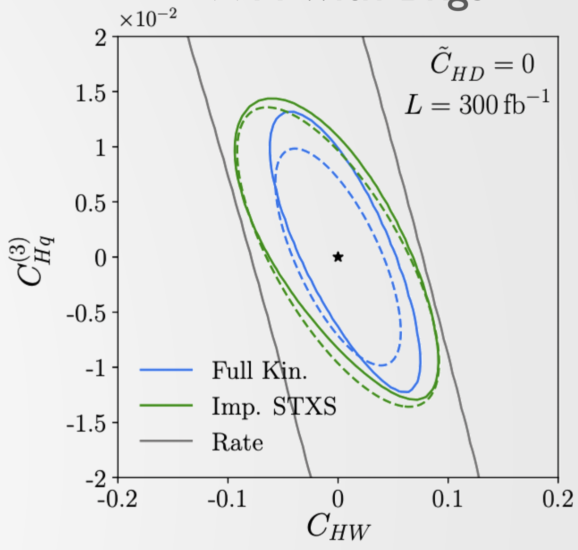
- Madminer: Neural networks based likelihood-free inference & related techniques
  - K. Cranmer , J. Pavez , and G. Louppe [1506.02169]
    J. Brehmer, K. Cranmer, G. Louppe, J. Pavez [1805.00013] [1805.00020] [1805.12244]
    J. Brehmer, F. Kling, I. Espejo, K. Cranmer [1907.10621]
  - J. Brehmer, S. Dawson, S. Homiller, F. Kling, T. Plehn [1908.06980]
  - A. Butter, T. Plehn, N. Soybelman, J. Brehmer [2109.10414]
  - established many of the *main ideas* & *statistical interpretation* in various *NN applications*
- Weight derivative regression (A.Valassi) [2003.12853]
- Parametrized classifiers for SM-EFT: NN with quadratic structure
- S. Chen, A. Glioti, G. Panico, A. Wulzer [*JHEP 05 (2021) 247*] [arXiv:2308.05704]
- Boosted Information Trees: Tree algorithms & boosting
  - S. Chatterjee, S. Rohshap, N. Frohner, R.S., D. Schwarz [2107.10859], [2205.12976]
- ML4EFT R. Ambrosio, J. Hoeve, M. Madigan, J. Rojo, V. Sanz [2211.02058]
- All approaches are "SMEFT-specific ML" with differences mostly on the practical side

WH with Bkgs



my practical experience

→ talk later today