hep-ph/2405.xxxxx

Constraining the Higgs Potential Shape with Machine Learning

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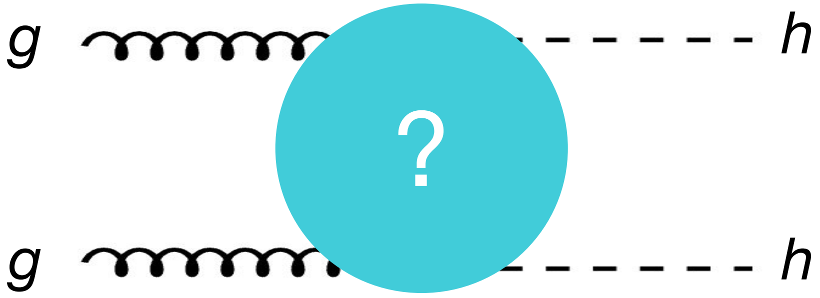
Our goal: measure the Higgs potential *V(Φ)*

$$-m^2(\phi^\dagger\phi)^2 + \lambda(\phi^\dagger\phi)^4 + \sum_i \frac{c_i}{\Lambda^{d_i-4}}\mathcal{O}_i$$

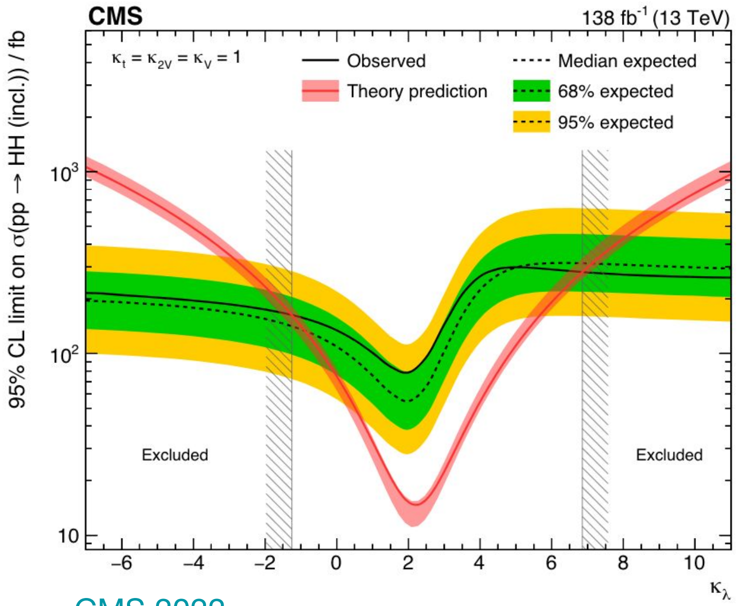
SM higgs

BSM Higgs
(SMEFT parameterization)

Concretely, we want to observe **dihiggs production** at the LHC

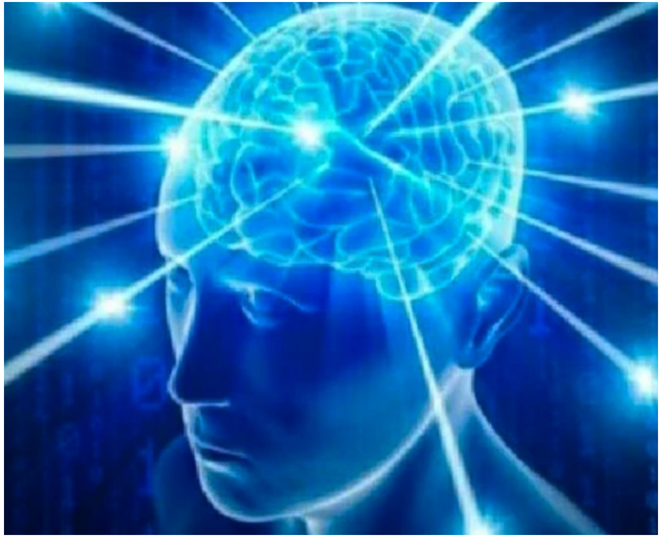


The past:
Cut and Count

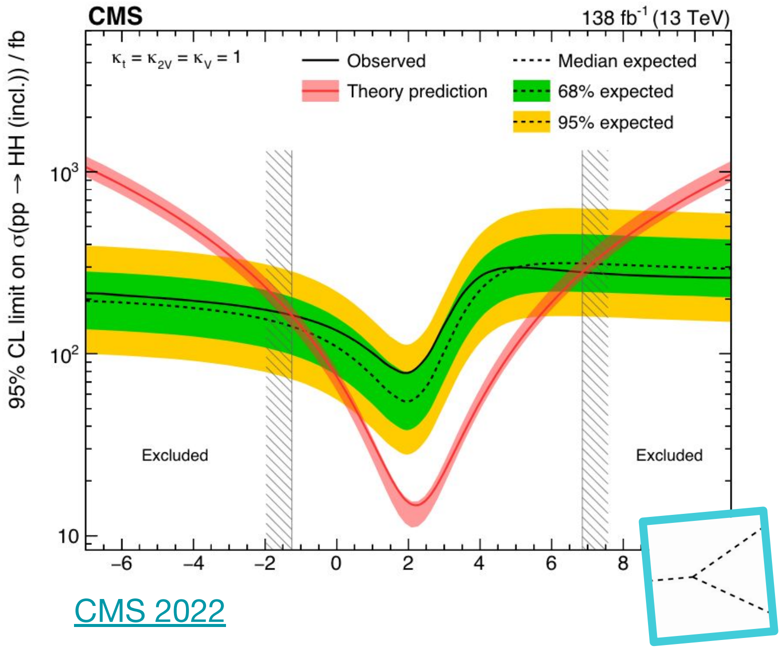


CMS 2022

The future (?):
Machine Learning

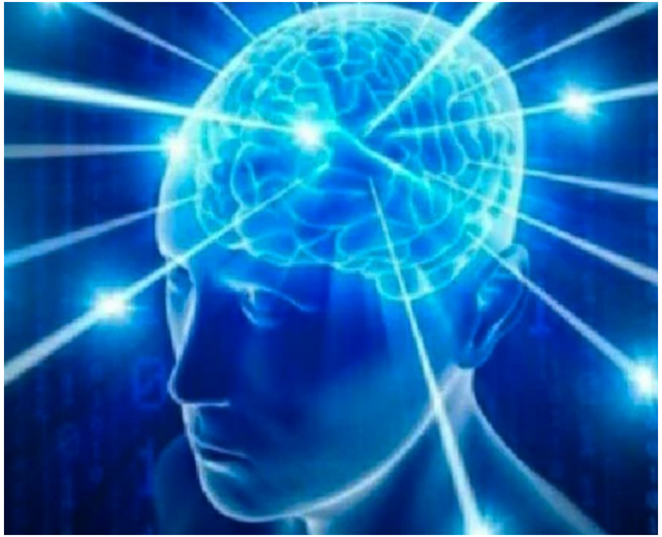


The past: Cut and Count



CMS 2022

The future (?): Machine Learning



The test statistic *q* now includes shape information

$$q(c|D) = q_{\text{rate}}(c|D) + q_{\text{shape}}(c|D)$$

$(c_\phi,\, c_{\phi d},\, c_{t\phi})$ Data

Likelihood ratio of
data | BSM hypothesis
to
data | SM hypothesis

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$(c_\phi,\ c_{\phi d},\ c_{t\phi})$ Data

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Likelihood ratio for
Poisson events
(cut and count)

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$(c_\phi, c_{\phi d}, c_{t\phi})$ Data

Likelihood ratio of
data | BSM hypothesis
to
data | SM hypothesis

Likelihood ratio for Poisson events (cut and count)

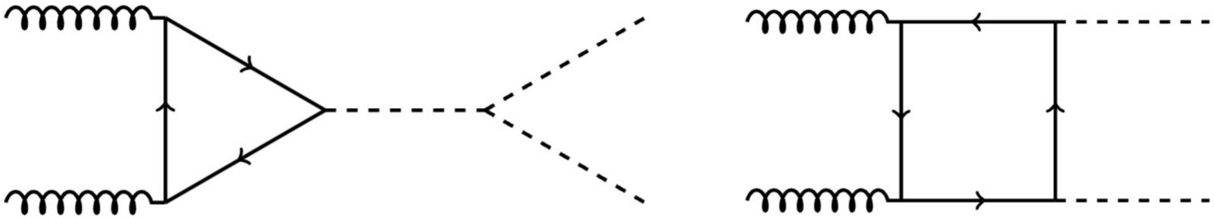
Likelihood ratio for shapes of kinematic distributions (machine learning)

SMEFT Operators in Detail

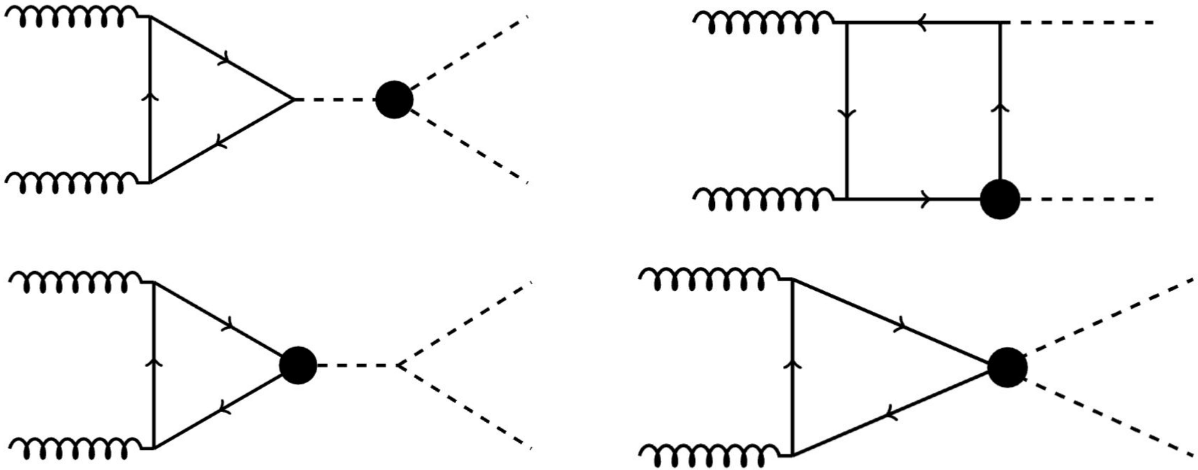
Symbol	Operator	Meaning
$\mathcal{O}_\phi$	$(\phi^\dagger\phi - \frac{v^2}{2})^3$	trilinear coupling
$\mathcal{O}_{\phi d}$	$\partial_\mu(\phi^\dagger\phi)\partial^\mu(\phi^\dagger\phi)$	dynamical coupling
$\mathcal{O}_{t\phi}$	$(\phi^\dagger\phi - \frac{v^2}{2})\overline{Q}t\tilde{\phi} + \text{h.c.}$	top-Yukawa coupling

These operators result in a zoo of diagrams…

SM diagrams



SMEFT diagrams

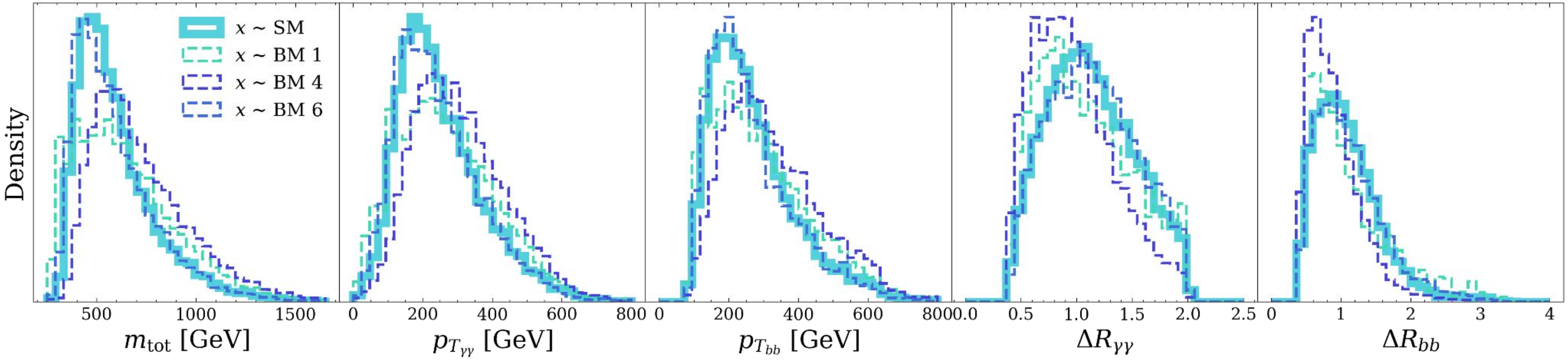


…whose inclusion changes the shapes of kinematic features

Our production channel: $hh \to bb\gamma\gamma$

Simulation pipeline: MadGraph (SMEFT@NLO model) → Pythia → Delphes

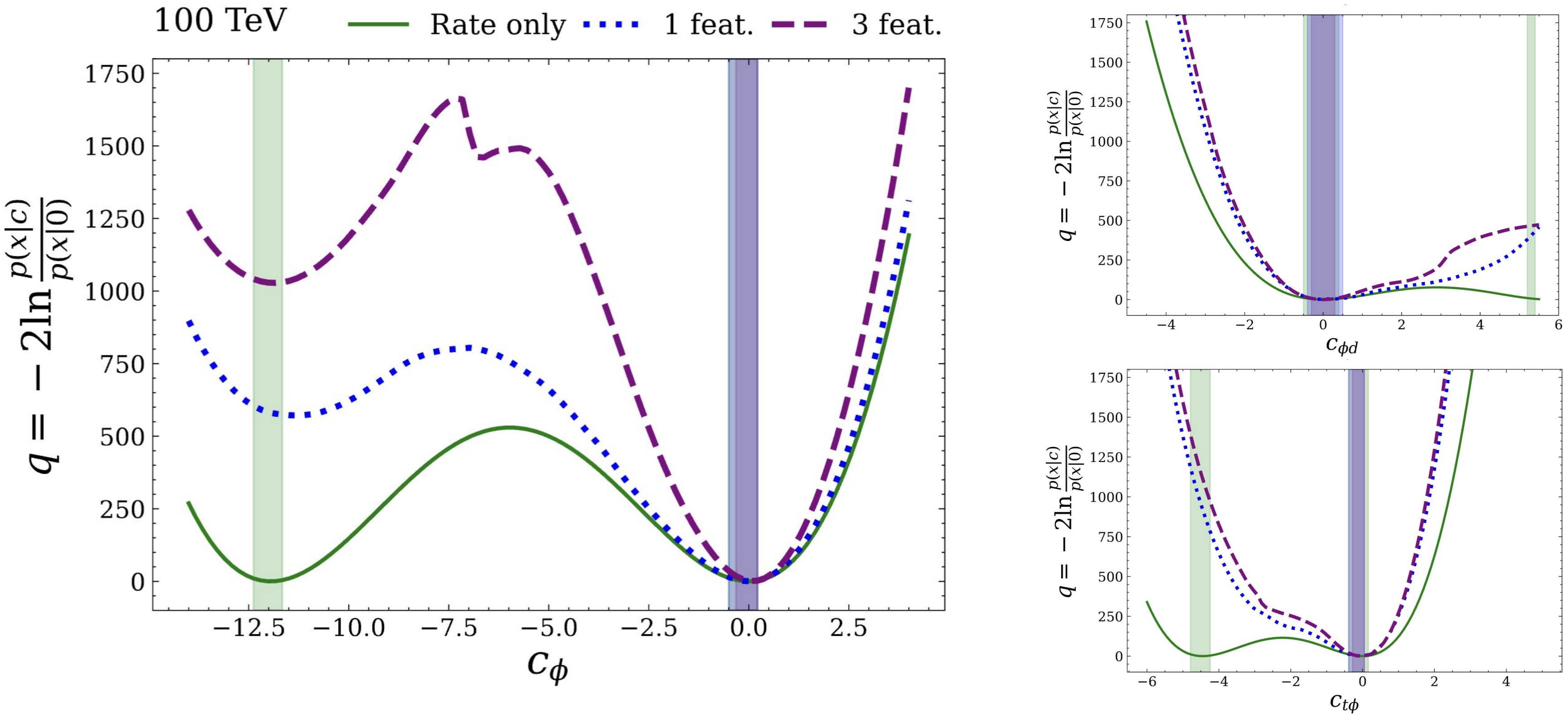
Collider setup: FCC-hh (100 TeV, 30/ab)



"BM" = shape benchmarks from 2304.01968

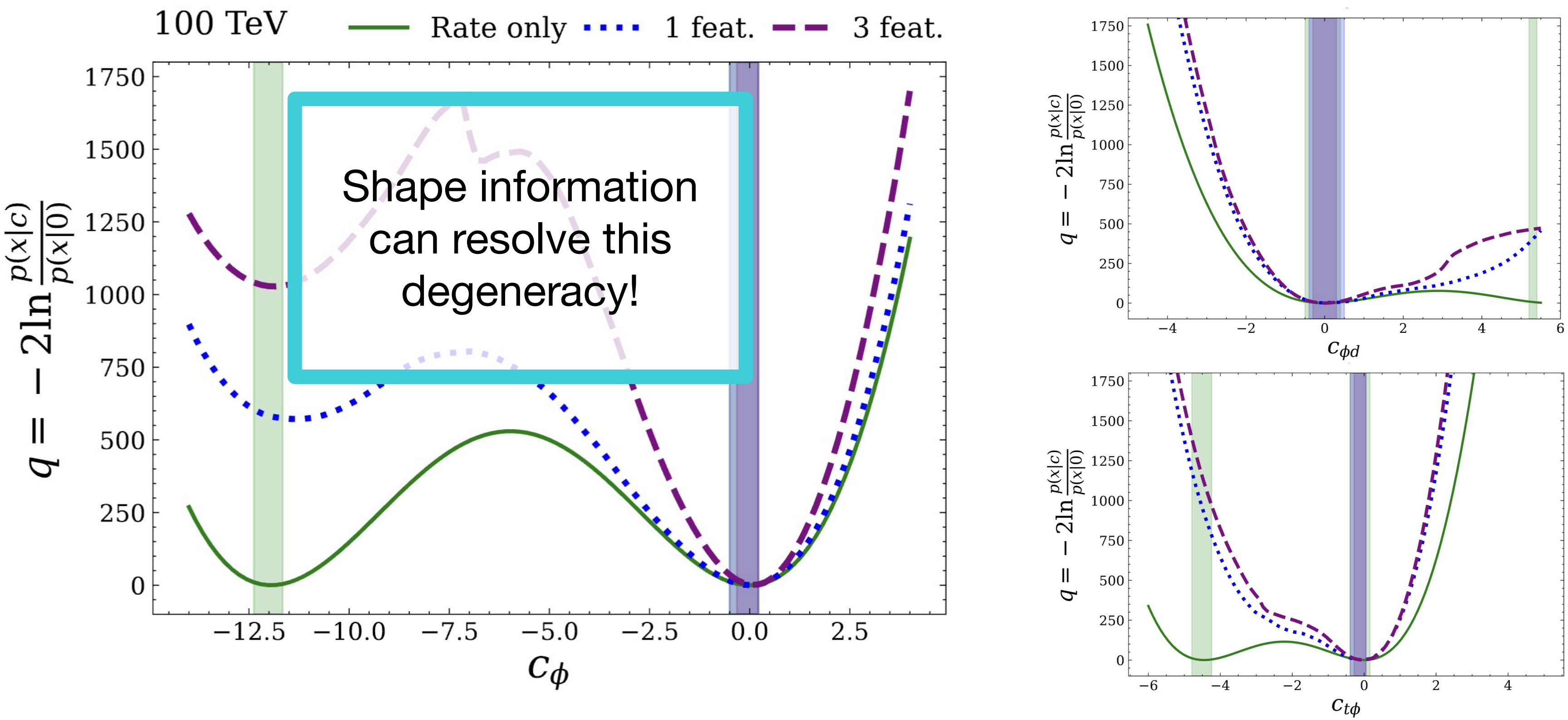
**see backups for background distribution

1D coupling coefficients can be recovered!



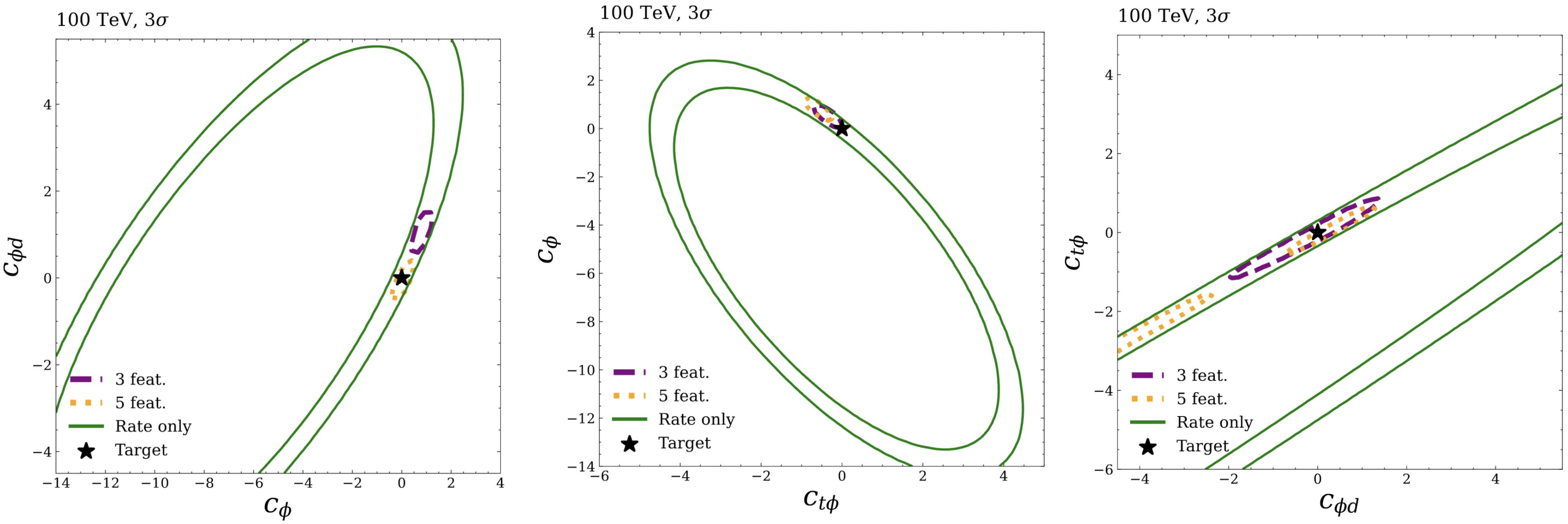
**see backups for HL-LHC projections

1D coupling coefficients can be recovered!



**see backups for HL-LHC projections

2D coupling coefficients can be recovered!



**see backups for HL-LHC projections

Summary

Adding shape information of kinematic observables to cut-and-count analyses can greatly improve their constraining power

Future investigations

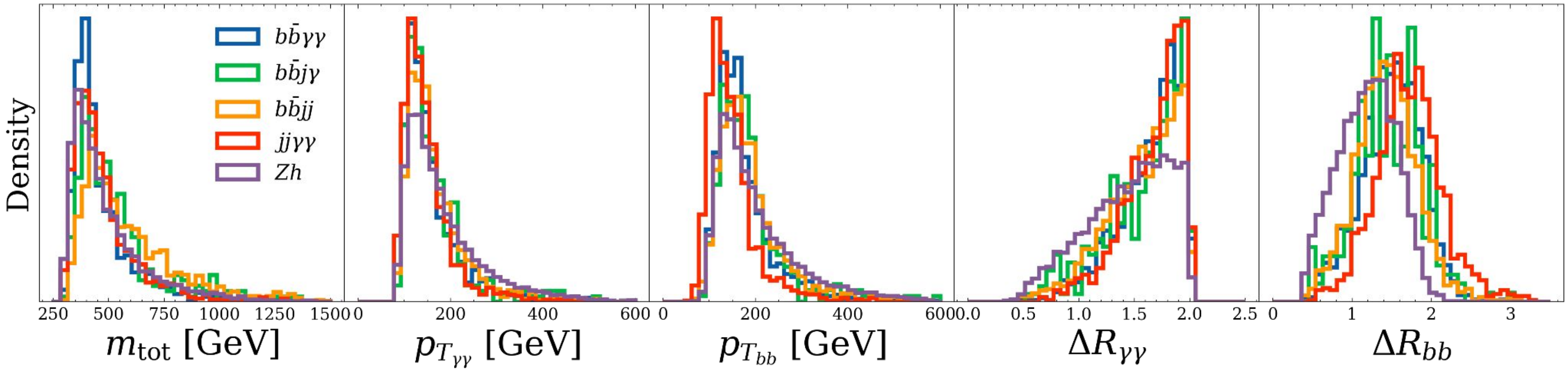
- More realistic background modeling (with uncertainties)
- Balancing signal-enhancing cuts and event preservation for classifier testing
- Expanding the Wilson coefficient space

Backup slides

SMEFT Operators in Detail

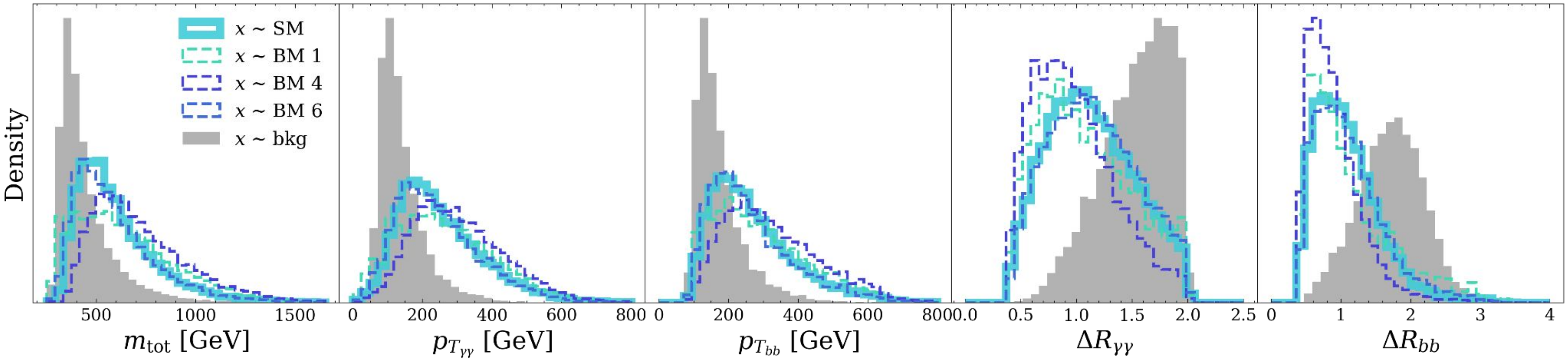
Operator	Explicit form
$\mathcal{O}_{\phi}$	$(\phi^\dagger\phi - \frac{v^2}{2})^3$
$\mathcal{O}_{\phi d}$	$\partial_\mu(\phi^\dagger\phi)\partial^\mu(\phi^\dagger\phi)$
$\mathcal{O}_{\phi D}$	$(\phi^\dagger D^\mu\phi)^\dagger(\phi^\dagger D_\mu\phi)$
$\mathcal{O}_{t\phi}$	$(\phi^\dagger\phi - \frac{v^2}{2})\overline{Q}t\tilde{\phi} + \text{h.c.}$
$\mathcal{O}_{\phi G}$	$(\phi^\dagger\phi - \frac{v^2}{2})G_A^{\mu\nu}G_{\mu\nu}^A$
$\mathcal{O}_{tG}$	$ig_s(\overline{Q}\tau^{\mu\nu}T_A t)\tilde{\phi}G_{\mu\nu}^A + \text{h.c.}$

Relevant background processes for dihiggs



- In this project, we use the *bbγγ* process as a proxy for all backgrounds
- Background feature shapes do not vary with the SMEFT coefficients c_{Φ}, $c_{\Phi d}$, $c_{t\Phi}$

Kinematic features with QCD background



- In this project, we use the *bbγγ* process as a proxy for all backgrounds
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The cut flow and event yields

	HL-LHC, 14TeV, $3ab^{-1}$				Future Collider, 100 TeV, $30ab^{-1}$			
	Signal		Background		Signal		Background	
	Events	Retention	Events	Retention	Events	Retention	Events	Retention
Start	257	100%	–	–	89,604	100%	–	–
+ tagging & efficiencies	95	37.1%	3.22×10^4	100%	29,600	33.0%	3.63×10^6	100%
+ kinematic cuts	49	18.9%	1.26×10^4	39.1%	11,100	12.3%	1.41×10^6	38.8%
+ m_h windows	15	5.89%	5.80×10^2	1.80%	3,950	4.40%	5.91×10^4	1.62%
+ angular cuts	13	4.92%	7.76×10^1	0.24%	3,600	4.02%	8.21×10^3	0.23%

$S/B \approx 0.16$

$S/B \approx 0.44$

Mixture models

To learn the likelihood ratio of *mixture models*, e.g.

data = signal (sig) + (bkg)

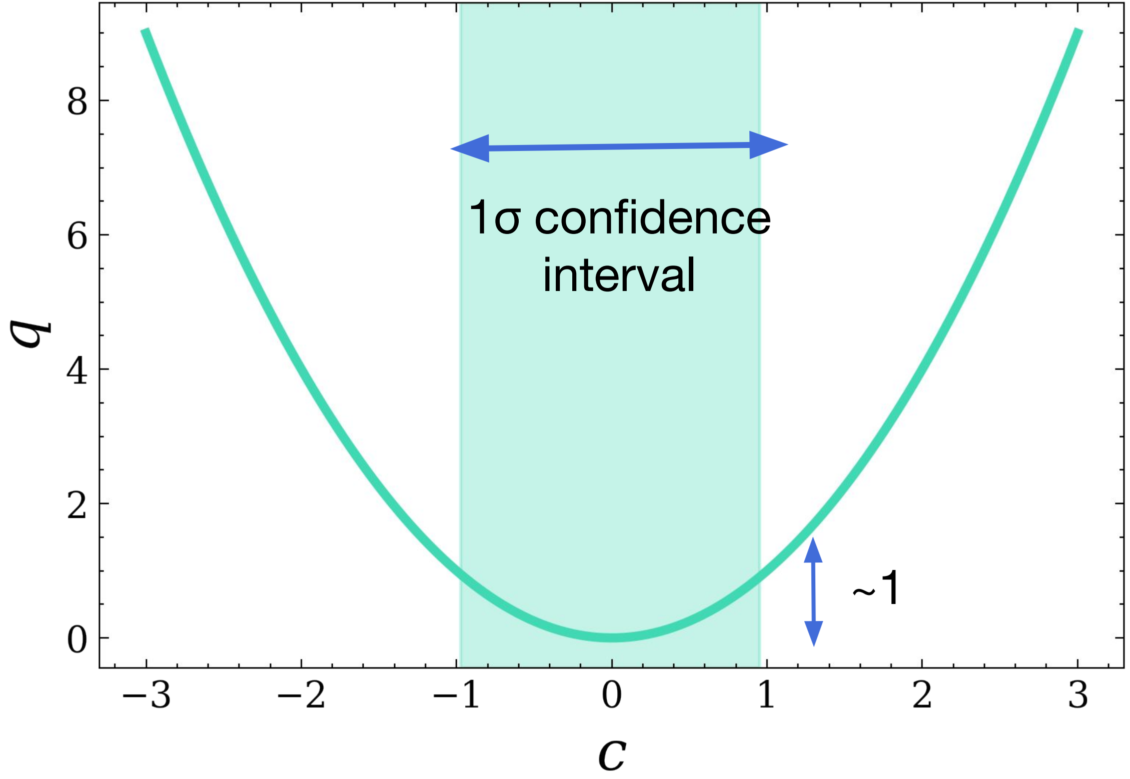
it is useful to decompose the *ratio of mixtures* into *sums of ratios of components*

$$\frac{\text{data 1}}{\text{data 0}} = \left(\frac{\text{sig 0}}{\text{sig 1}} + \frac{\text{bkg 0}}{\text{sig 1}} \right)^{-1} + \left(\frac{\text{sig 0}}{\text{bkg 1}} + \frac{\text{bkg 0}}{\text{bkg 1}} \right)^{-1}$$

These component ratios are much easier for classifiers to learn!

Constructing confidence intervals from *q*

$$q(c|D) = -2\ln\left(\frac{p(D|c)}{p(D|c=0)}\right)$$



Neural networks and training

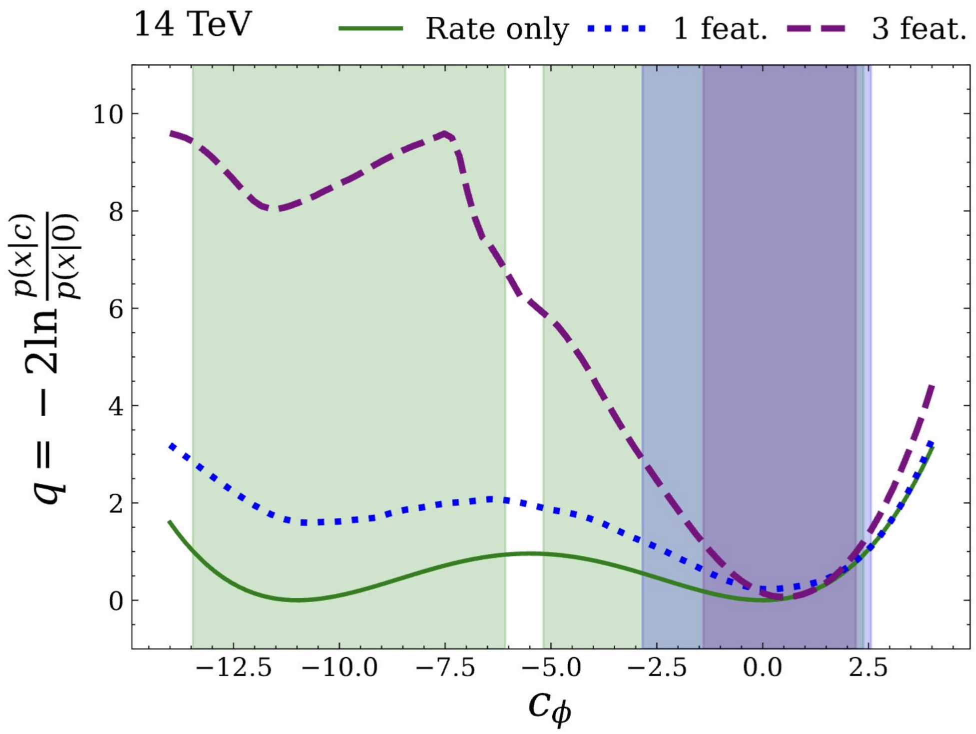
Architecture: Dense Neural Networks with 2 layers of 32 nodes

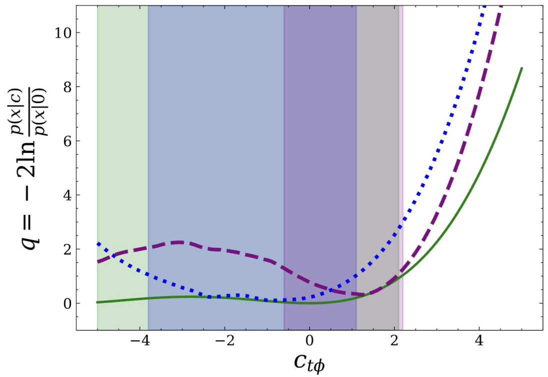
Training: batch size of 1024, weight decay 1e-4, learning rate of 1e-3 that reduces if the validation loss stagnates. Train until validation loss stagnates for 20 epochs.

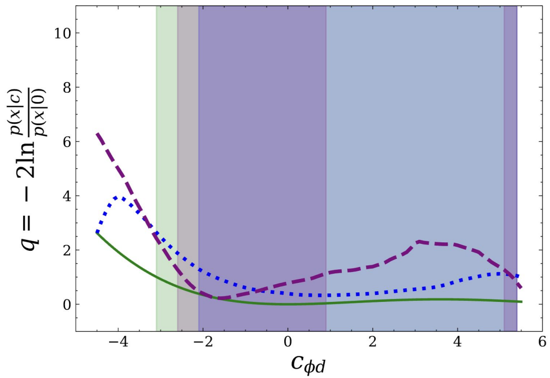
Train-val split: 80-20

To mitigate the stochastic nature of network training, we ***ensemble*** *the outputs of five networks with different initial random seeds.*

14 TeV Results: 1D







14 TeV Results: 2D