

Observables for EFT Measurements

Andrei Gritsan

Johns Hopkins University



April 25, 2024

[LPC EFT Workshop at Notre Dame](#)

University of Notre Dame, Indiana

Observables in the Context of EFT fits

CERN-LHCEFTWG-2022-001

CERN-LPCC-2022-05

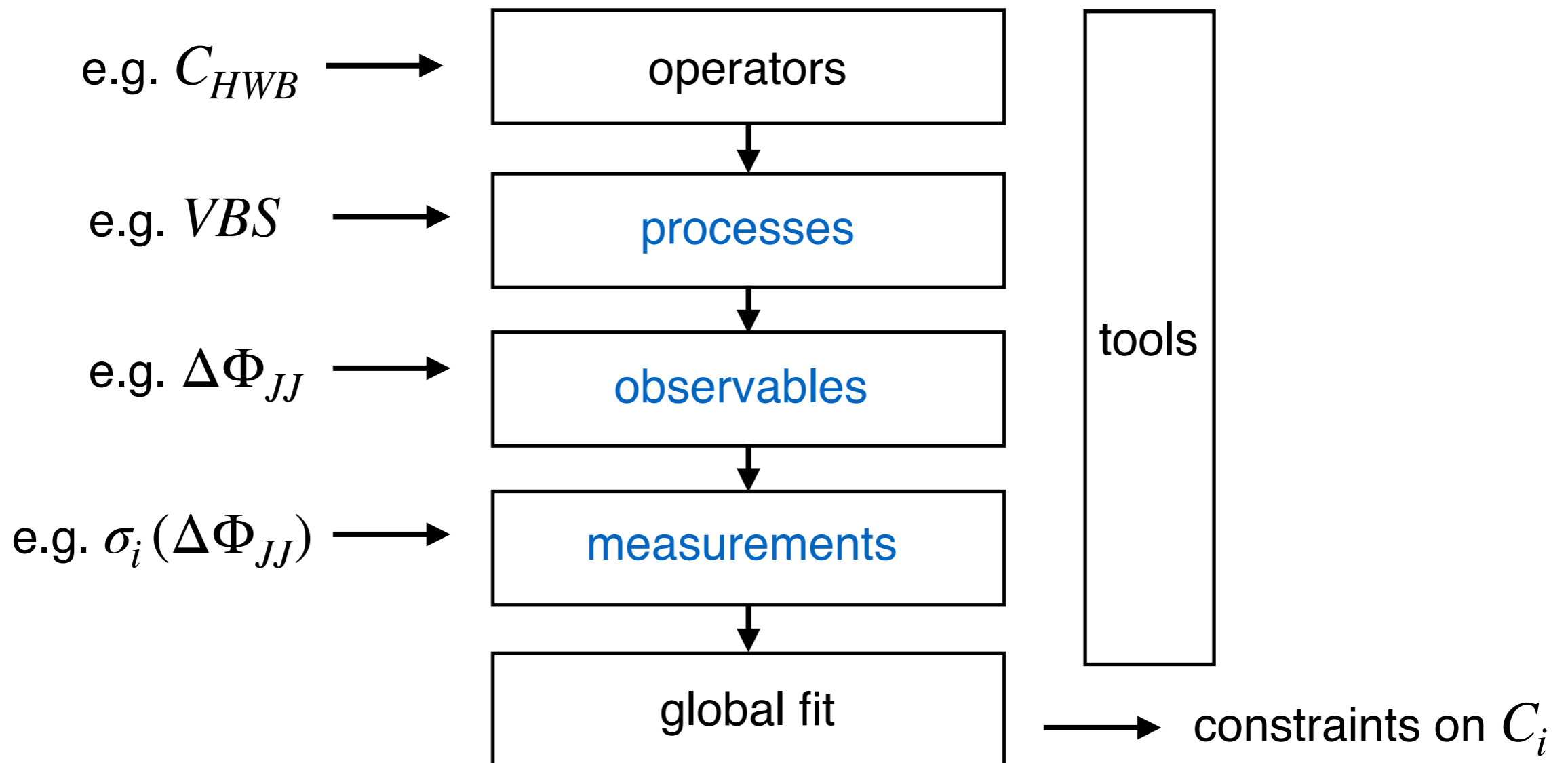
November 15, 2022

- LHC EFT WG effort (Area 3):

[arXiv:2211.08353](https://arxiv.org/abs/2211.08353)

LHC EFT WG Report: Experimental Measurements and Observables

Nuno Castro¹, Kyle Cranmer², Andrei V. Gritsan³, James Howarth⁴, Giacomo Magni^{5,6}, Ken Mimasu⁷, Juan Rojo^{5,6}, Jeffrey Roskes³, Eleni Vryonidou⁸, Tevong You^{9,10,11}



Observables

measurements

observables

processes

$$\mathcal{P}(\vec{x}_{\text{reco}} | \vec{\theta})$$

reco observables

$$\vec{x}_{\text{reco}}$$

measurement

$$= \int d\vec{x}_{\text{part}} p(\vec{x}_{\text{reco}} | \vec{x}_{\text{part}})$$

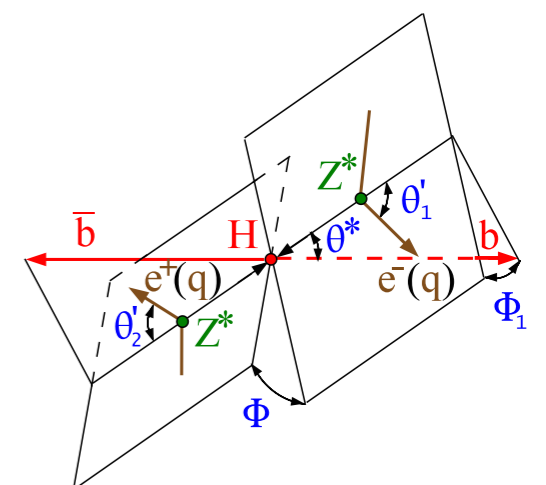
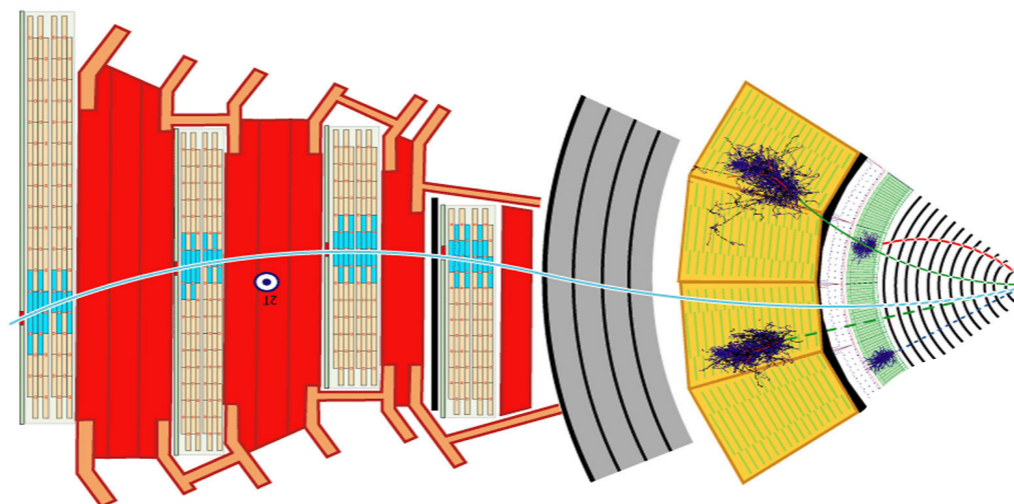
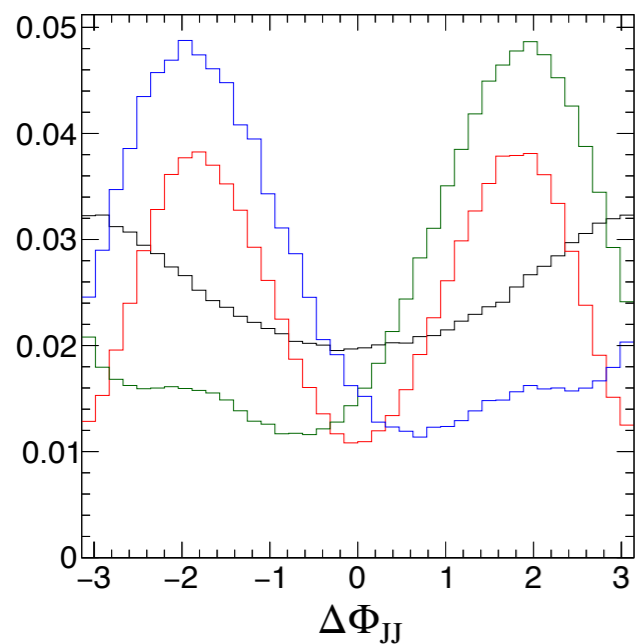
parton shower
detector effects
reconstruction

$$\mathcal{P}(\vec{x}_{\text{part}} | \vec{\theta})$$

hard process
matrix elements

EFT params $\vec{\theta}$

parton mom \vec{x}_{part}



Observables

$$\mathcal{P}(\vec{x}_{\text{reco}} | \vec{\theta}) = \int d\vec{x}_{\text{part}} p(\vec{x}_{\text{reco}} | \vec{x}_{\text{part}}) \mathcal{P}(\vec{x}_{\text{part}} | \vec{\theta})$$

reco
observables

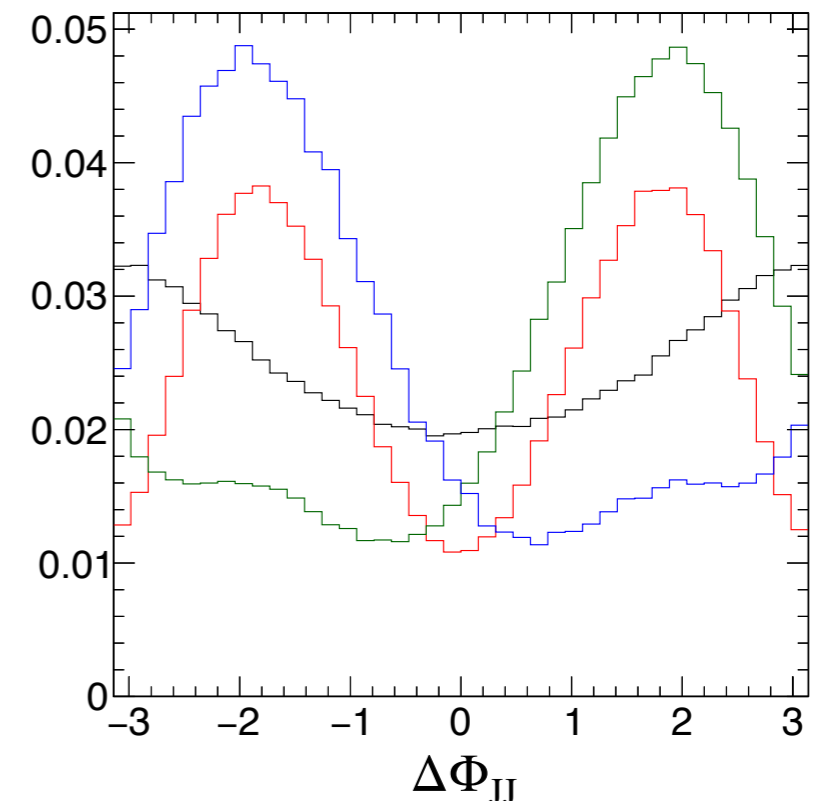
- typical **SM observables** (to suppress background)
- **EFT-sensitive** observables (e.g. angular, q^2 , etc)
- **optimized observables** (matrix element, machine learning)
- **full accessible information** $\vec{x}_{\text{reco}}^{\text{full}}$ (e.g. all four-vectors)

Example: VBF $\Delta\Phi_{JJ}$ (**EFT-sensitive**)

EFT:

- new tensor structures
- higher q dimensions

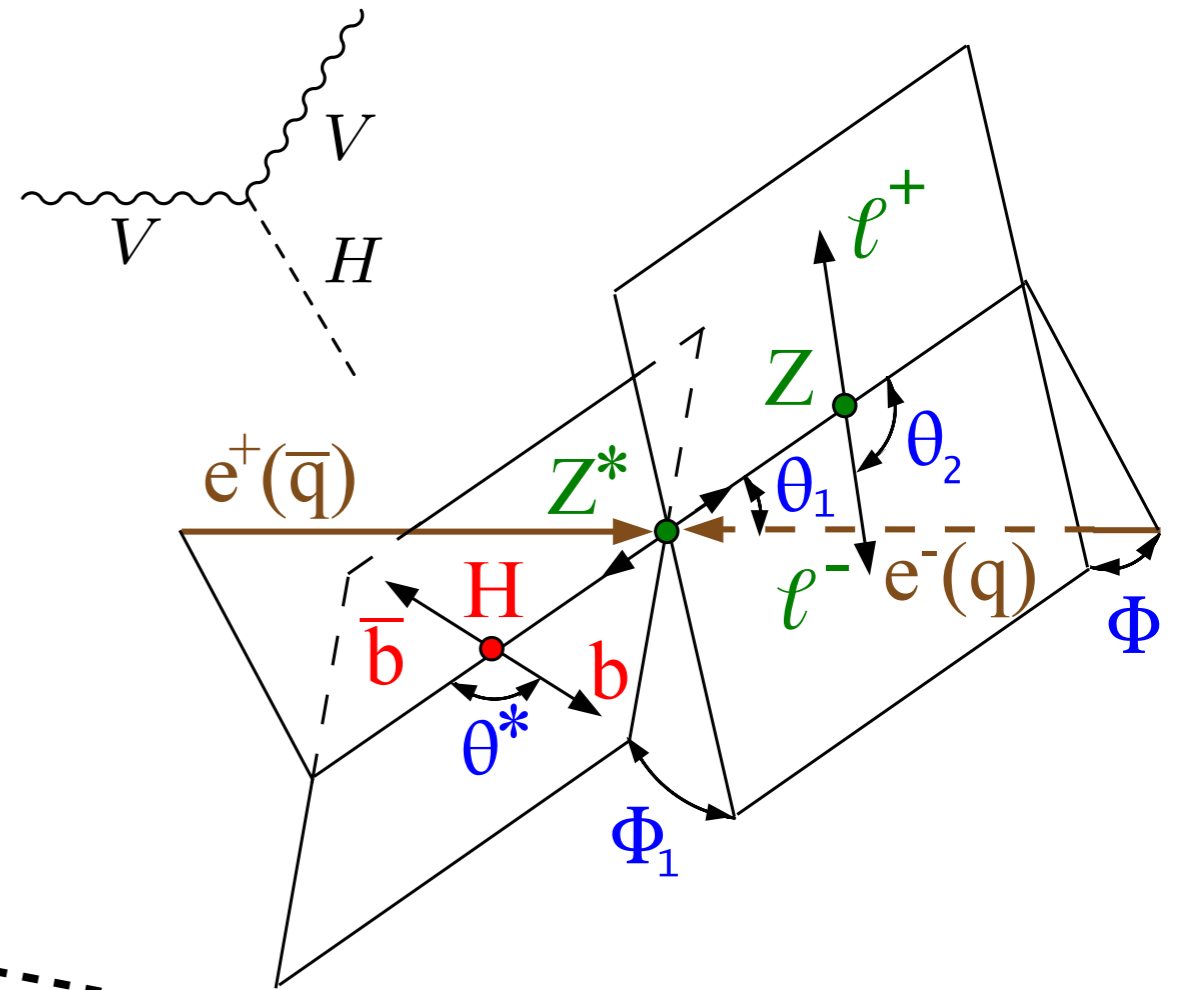
SM	—	$(\theta_0, 0)$
CP-odd	—	$(0, \theta_1)$
+mix	—	$(\theta_0, +\theta_1)$
-mix	—	$(\theta_0, -\theta_1)$



Observables

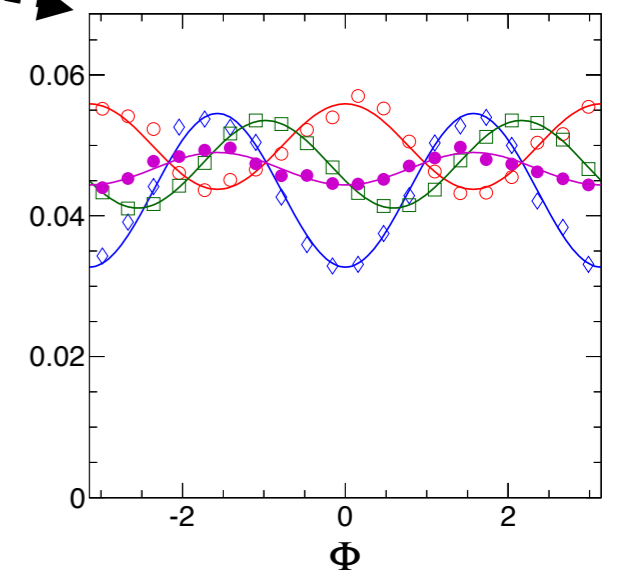
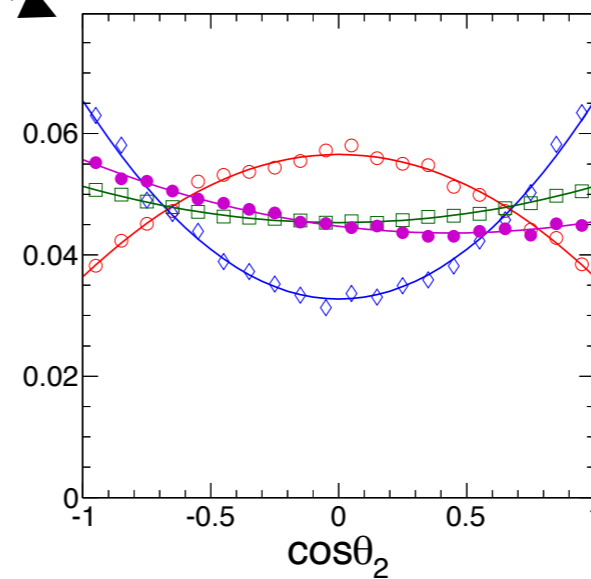
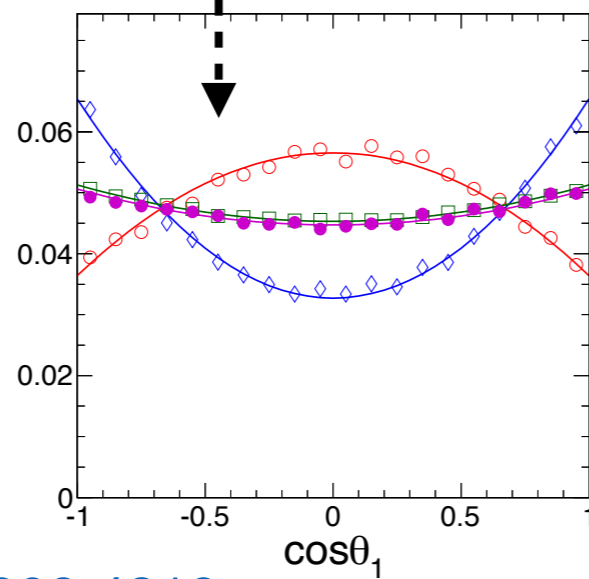
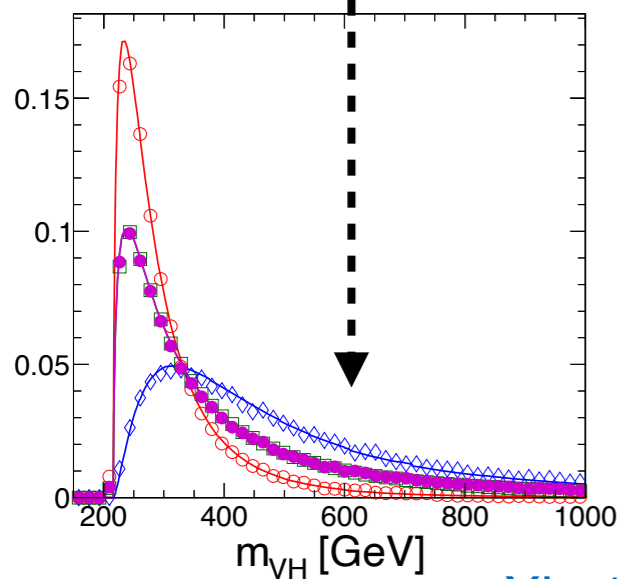
Example: VH process on LHC

- full information $\vec{\chi}_{\text{reco}}^{\text{full}}$: take all below
- SM observables: e.g. m_{bb} , $m_{\ell\ell}$
(useless for EFT)
- EFT-sensitive observables



q^2 -enhancement

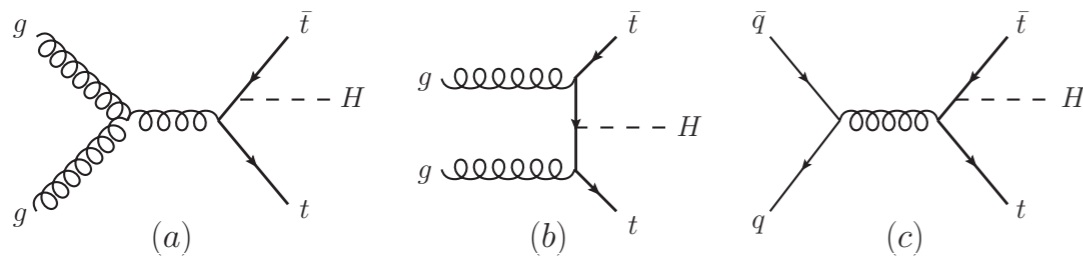
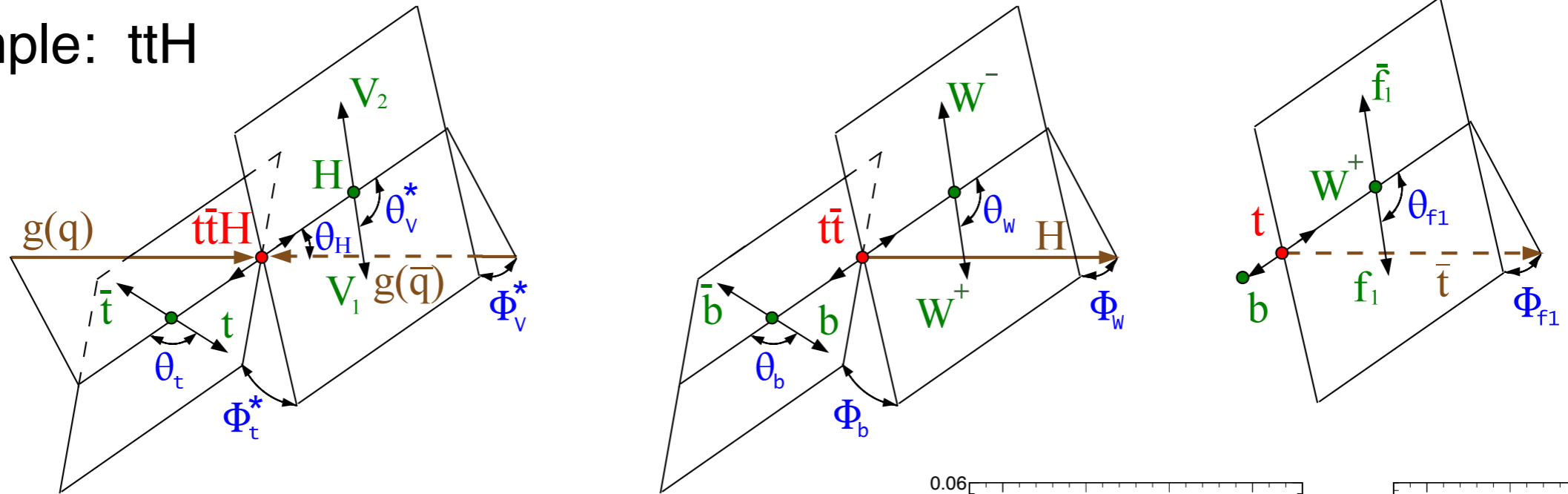
angular



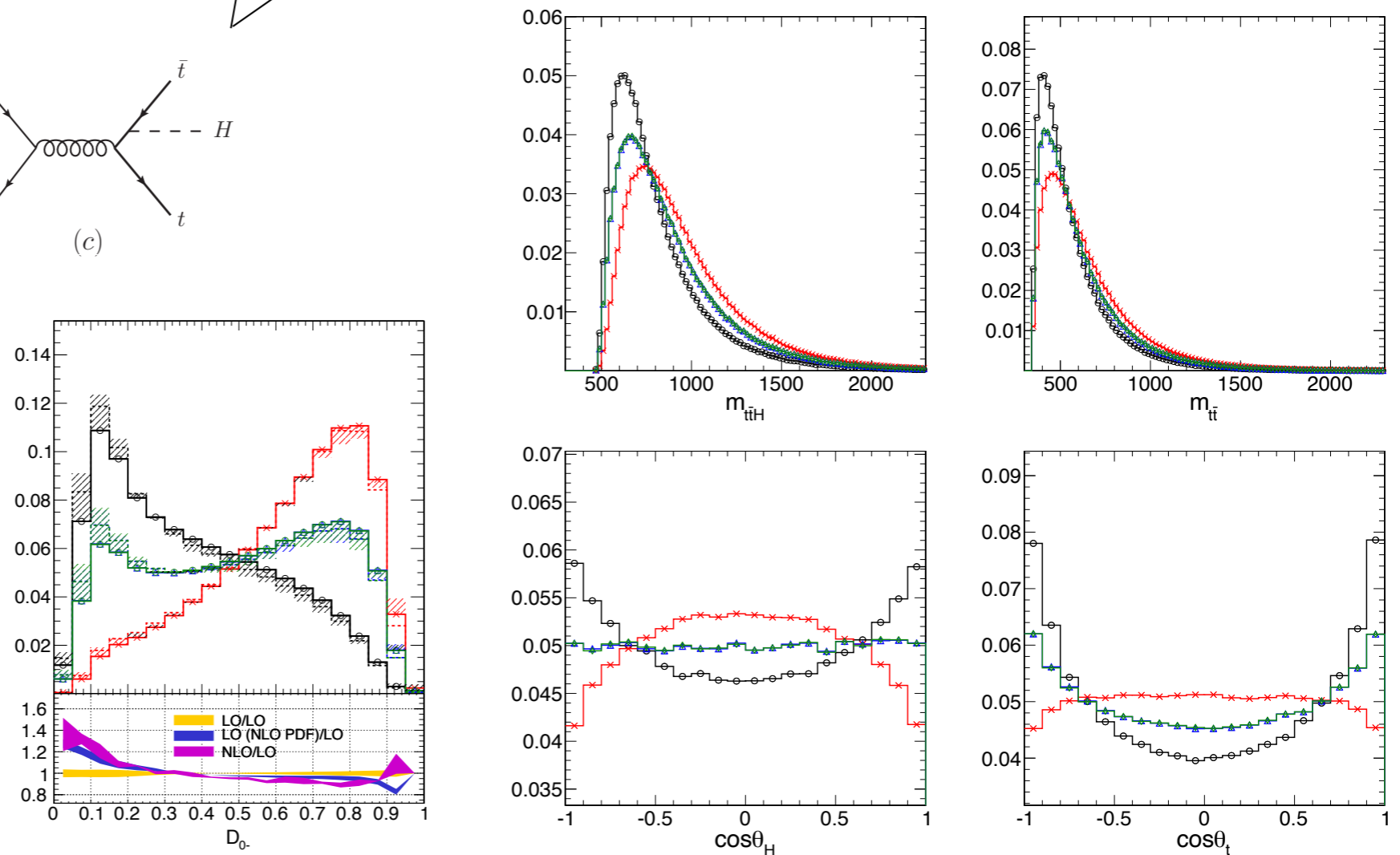
[arXiv:1309.4819](https://arxiv.org/abs/1309.4819)

Observables

Example: ttH



- ~20 observables
- ~1 optimal observable if consider 2 Operators (κ_t VS $\tilde{\kappa}_t$)

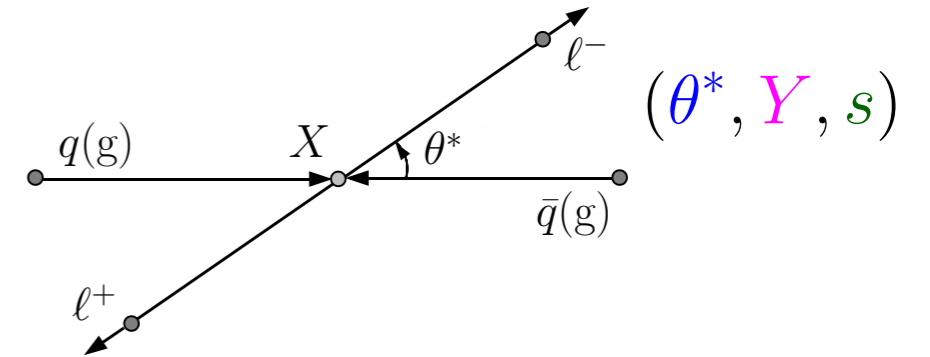


[arXiv:1606.03107](https://arxiv.org/abs/1606.03107)

Measurement: “Matrix Element Method”

- “Best” measurement: — full accessible information $\vec{x}_{\text{reco}}^{\text{full}}$ (e.g. 4-vectors)

- Example: 1st $\sin^2 \theta_W$ on LHC ([arXiv:1110.2682](https://arxiv.org/abs/1110.2682))

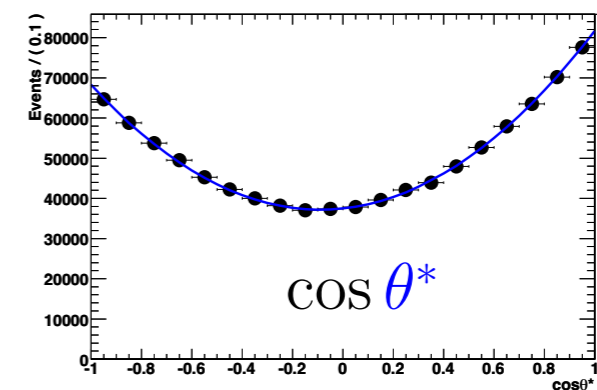
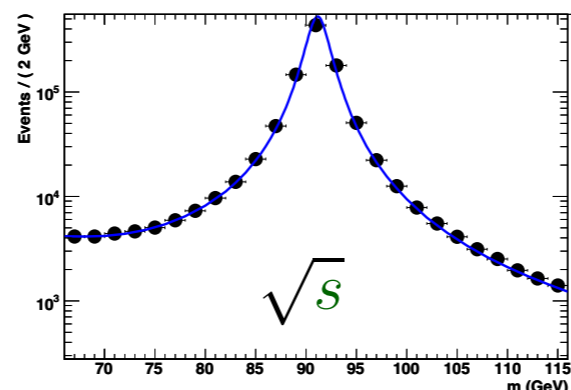
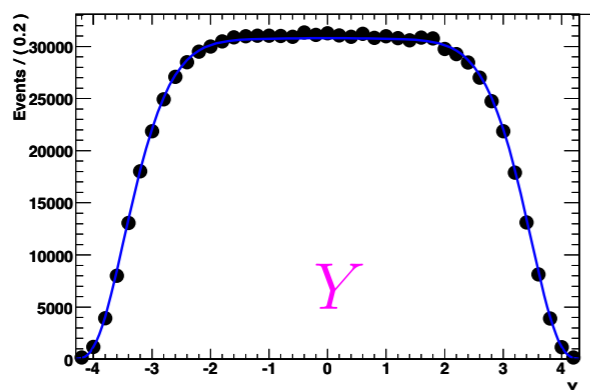


— hard process “matrix elements” (MEM)

$$\frac{d\sigma_{pp}(Y, s, \theta^*)}{dY ds d\cos\theta^*} \propto \frac{1}{s_{pp}} \sum_{q=uds cb} \hat{\sigma}_{q\bar{q}}(s, \theta^*) \tilde{f}_q \left(e^Y \sqrt{s/s_{pp}}, s \right) \tilde{f}_{\bar{q}} \left(e^{-Y} \sqrt{s/s_{pp}}, s \right)$$

— detector effects, reconstruction depends on $\sin^2 \theta_W$ & C_i

$$\mathcal{P}_{\text{detect}}(\theta^*, Y, s) = \mathcal{G}(\theta^*, Y, s) \times \int_{-\infty}^{+\infty} dx \mathcal{R}(x) \mathcal{P}_{\text{observe}}(Y, s - x, \theta^*)$$



[thesis](#) of
N. Tran

Measure: MEM and Simulation-Based Inference

- not the same as **optimized observables** (though can be used to compute):
 - ME or ML **observables** can be used in any approach (e.g. differential)
- Matrix Element Method (**MEM**) — compute the likelihood from first principles

$$\mathcal{P}(\vec{x}_{\text{reco}} | \vec{\theta}) = \int d\vec{x}_{\text{part}} p(\vec{x}_{\text{reco}} | \vec{x}_{\text{part}}) \mathcal{P}(\vec{x}_{\text{part}} | \vec{\theta})$$

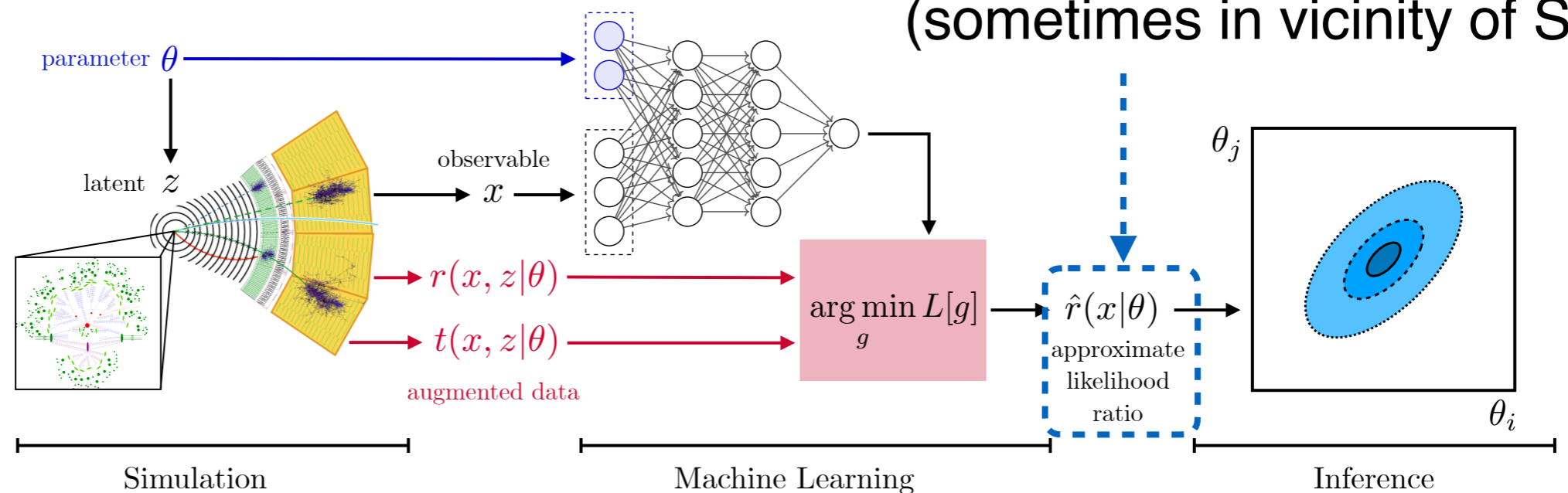
← full info

ideal for EFT, but: **hard to model** transfer function p , **ME not available** for all processes...
 popular in Flavor, few examples in EW, top, Higgs (e.g. backgrounds)

- Simulation-based (**ML**) inference

— learn the full likelihood ratio (sometimes in vicinity of SM)

see talk by Harrison Prosper



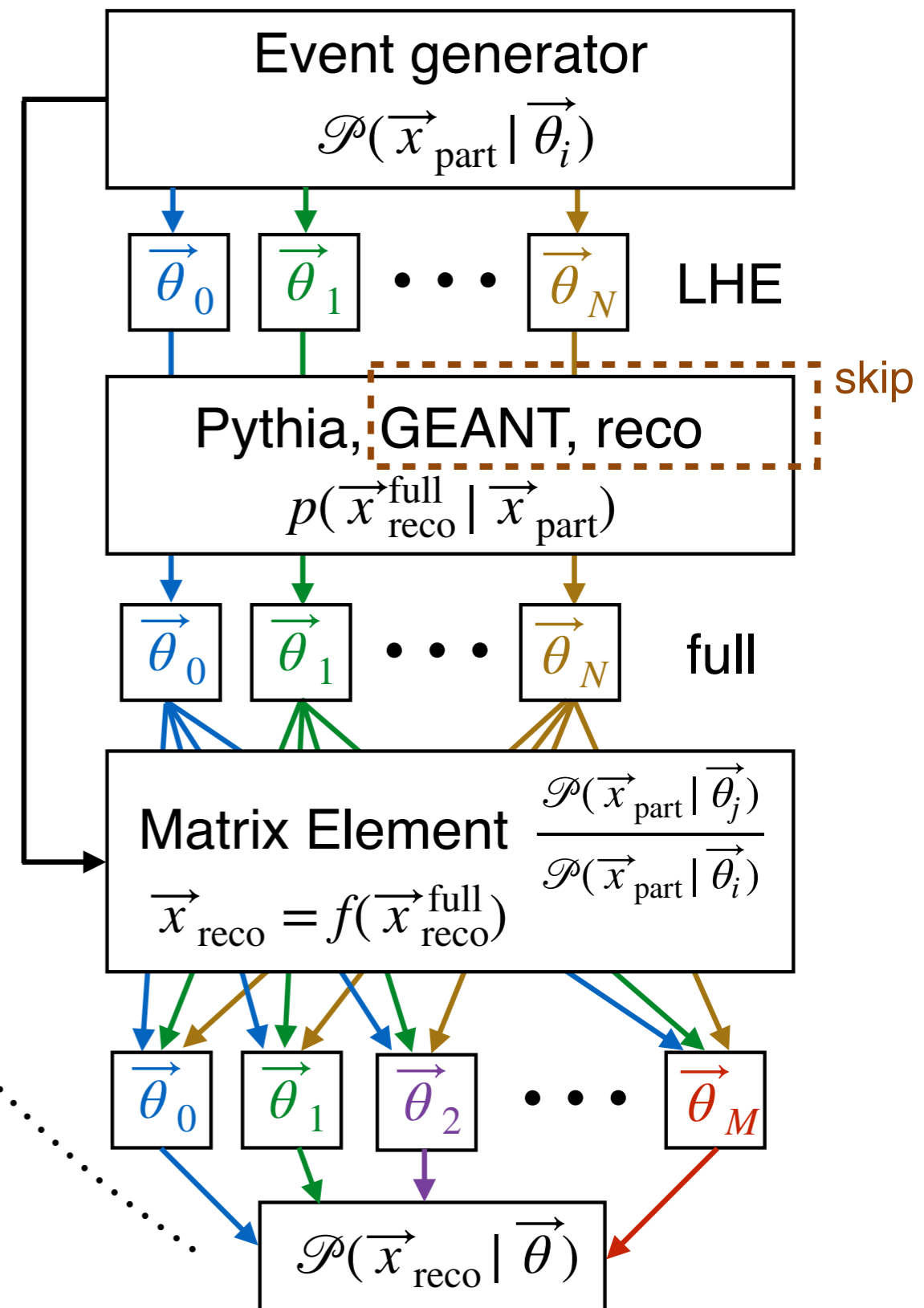
Measurements: Template fit

MEM and ML aside:

- most measurements are based on templates of Observables $\mathcal{P}_k(\vec{x}_{\text{reco}})$

$$\mathcal{P}(\vec{x}_{\text{reco}} | \vec{\theta}) \propto \mathcal{P}_0(\vec{x}_{\text{reco}}) + \sum_k \left(\frac{2\theta_k}{\theta_0} \right) \mathcal{P}_k(\vec{x}_{\text{reco}}) + \dots$$

- **Single-step** (folded)
 - can be **optimal** and **unbiased**
 - most **difficult** and **no re-interpretation**
 - example: direct fullsim fit for θ_i
- **Two-step** (unfolded)
 - **easier** and open for **re-interpretation**
 - **not full information**, SM **assumption**
 - example: differential, STXS



Observables for Unfolded Measurements

- Differential cross sections — detector corrected measurement
 - historically **tools for theorists** to test calculations and MC tuning
 - more recently **EFT applications** — as step-1 in interpretation (shape dependence of Observables)
- Considerations for Observables:
 - best with **diagonal response matrix** in the **unfolding** procedure
 - best with **flat acceptance effects**: **biased to SM** in unfolding — often small
step-1: “unfold” to parton-level distribution

$$\mathcal{P}(\vec{x}_{\text{reco}}|\vec{\theta}) = \int d\vec{x}'_{\text{part}} p'(\vec{x}_{\text{reco}}|\vec{x}'_{\text{part}};\vec{\theta}) \mathcal{P}(\vec{x}'_{\text{part}}|\vec{\theta})$$

usually assume **SM** θ_0

$\vec{x}'_{\text{part}} \subset \vec{x}_{\text{part}}$

- often exclude **optimized Observables**, but some examples exist
- EFT effect in **background** — best with **high S/B**

Which Observables to use?

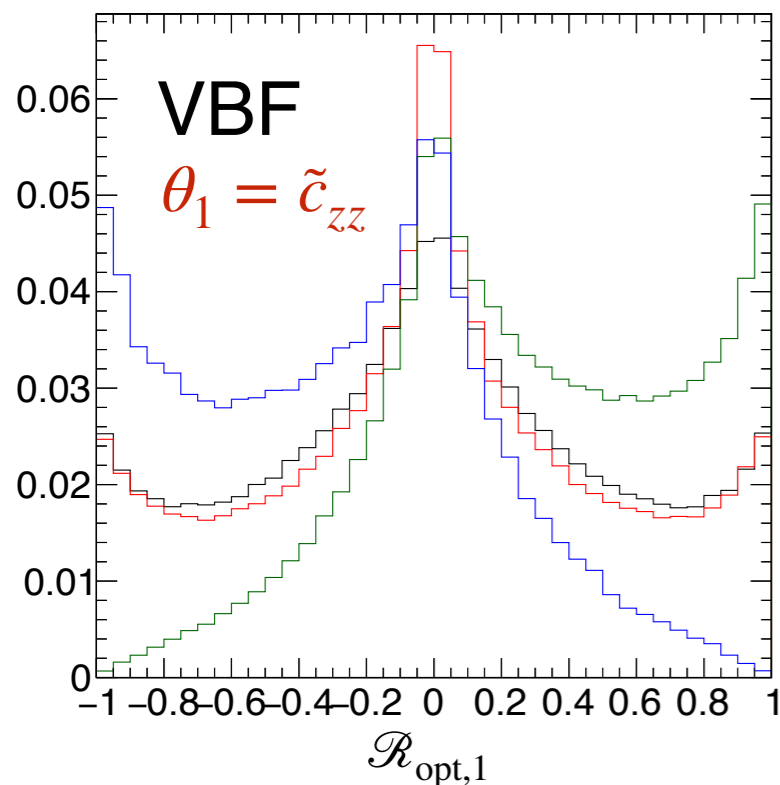
- typical **SM observables** (to suppress background)
 - **EFT-sensitive** observables (e.g. angular, q^2 , etc)
 - **optimized observables** (matrix element, machine learning)
 - **full accessible information** $\vec{x}_{\text{reco}}^{\text{full}}$ (e.g. all four-vectors)
- **full information** is the best, input to MEM, ML
but hard to deal with $ND, N \gg 1$, e.g. in templates
 - **optimized Observables**: pack **full information** in $1D$ optimal for **one target**
works if the number of targets is small (e.g. most sensitive C_i)
 - **SM** or **EFT observables**: most often used in the unfolded measurements
as input to step-2
 - **observable** choice does not limit its usage
(e.g. **differential measurement** of an **optimized Observable** is an option)

Illustration of Observables

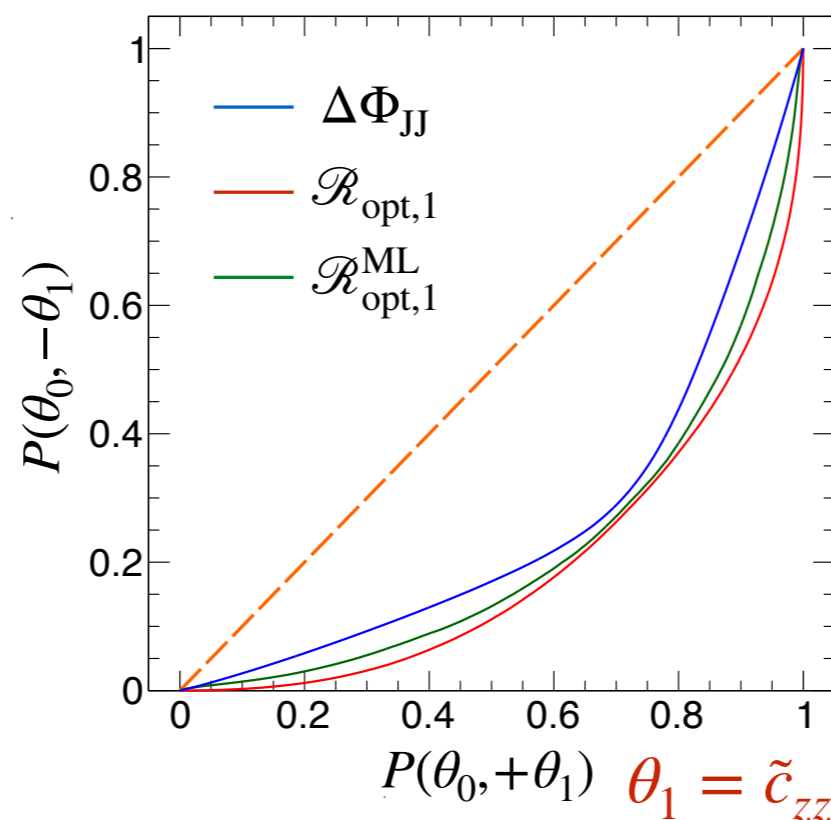
- typical **SM observables** (to suppress background)
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Performance

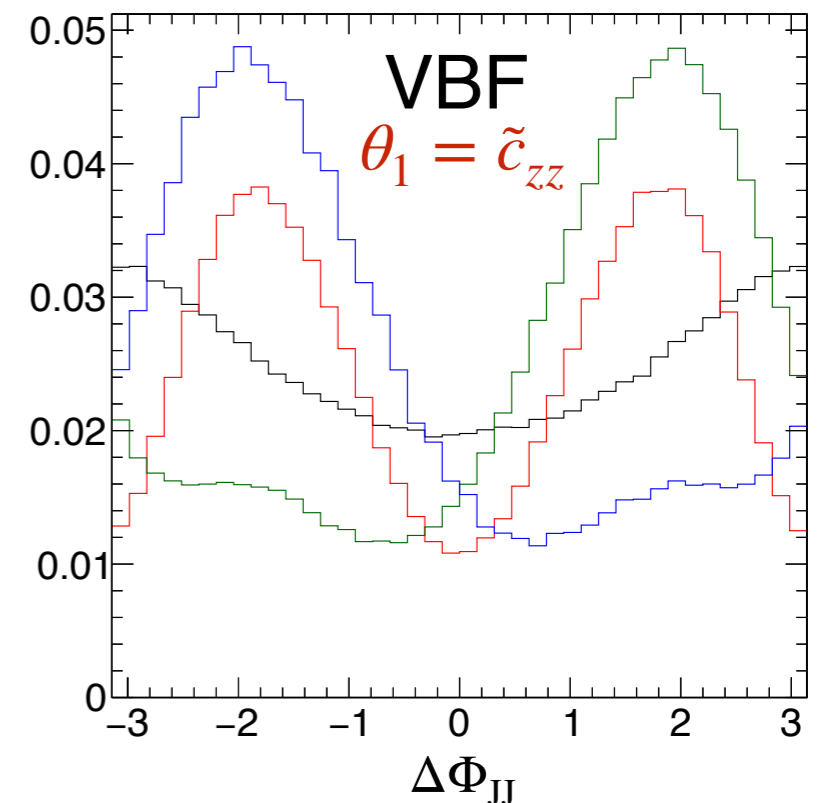
optimal Observable



application to $\theta_1 = \tilde{c}_{zz}$



EFT observable



Optimized Observables: type 2

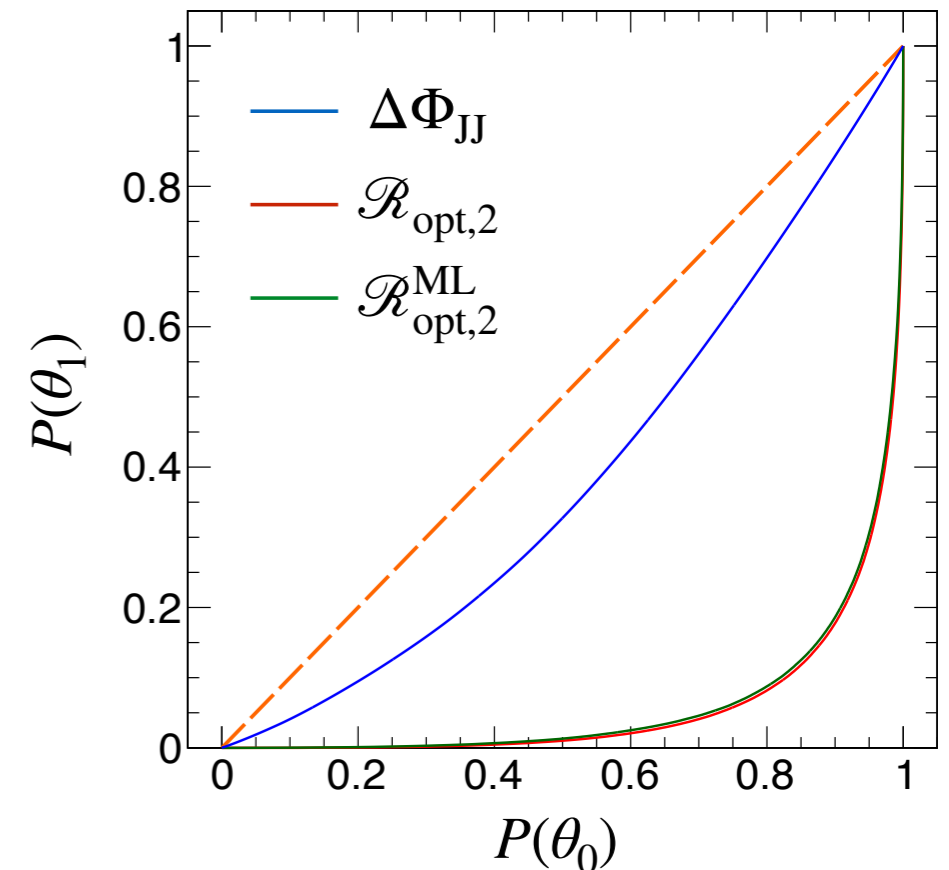
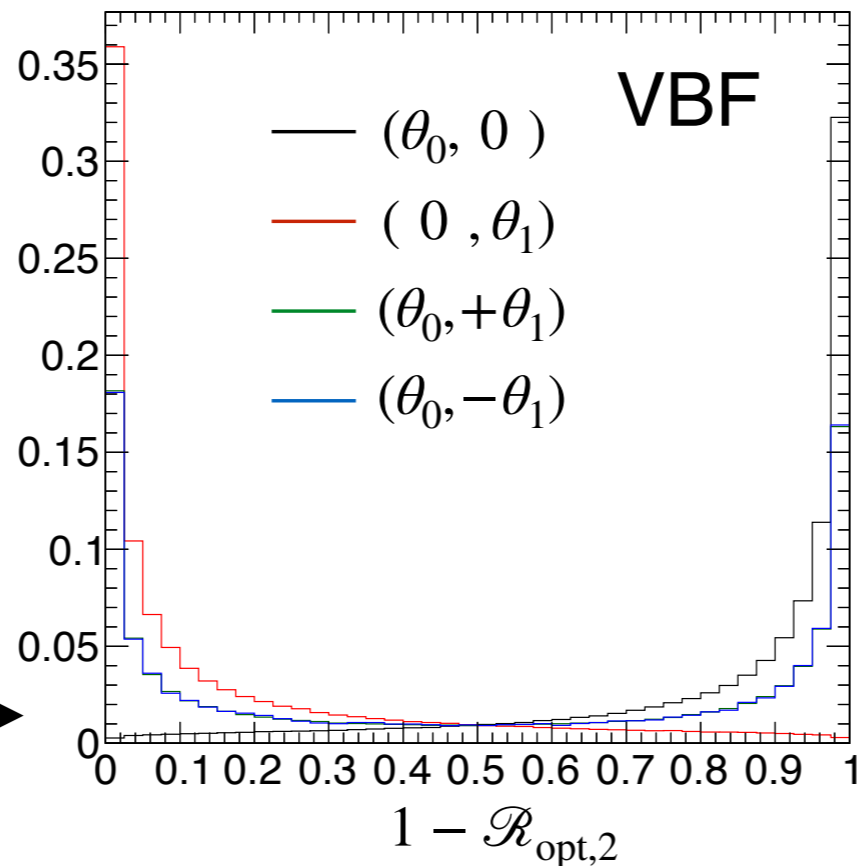
$$\mathcal{P}(\vec{x}_{\text{reco}} | \vec{\theta}) \propto \mathcal{P}_0(\vec{x}_{\text{reco}}) + \sum_k \left(\frac{2\theta_k}{\theta_0} \right) \mathcal{P}_{0k}(\vec{x}_{\text{reco}}) + \sum_k \left(\frac{\theta_k}{\theta_0} \right)^2 \mathcal{P}_k(\vec{x}_{\text{reco}}) + \sum_{i<j} \left(\frac{2\theta_i\theta_j}{\theta_0^2} \right) \mathcal{P}_{ij}(\vec{x}_{\text{reco}})$$

$$\mathcal{R}_{\text{opt},2} = \frac{\mathcal{P}_1(\vec{x}_{\text{reco}}^{\text{full}})}{\mathcal{P}_0(\vec{x}_{\text{reco}}^{\text{full}}) + c \cdot \mathcal{P}_1(\vec{x}_{\text{reco}}^{\text{full}})}$$

$\mathcal{P}_0, \mathcal{P}_1$
“matrix elements”
for models θ_0, θ_1

- **Type-2 Optional Observable** with Matrix Elements:
 - classical **signal-to-background**
 - in EFT: **SM term** vs. **quadratic term**

- ML equivalent:
parton shower,
detector effects
train against 2 samples



e.g. in VBF: $\theta_1 = \tilde{c}_{zz}$

Optimized Observables: type 1

$$\mathcal{P}(\vec{x}_{\text{reco}} | \vec{\theta}) \propto \mathcal{P}_0(\vec{x}_{\text{reco}}) + \sum_k \left(\frac{2\theta_k}{\theta_0} \right) \mathcal{P}_{0k}(\vec{x}_{\text{reco}}) + \sum_k \left(\frac{\theta_k}{\theta_0} \right)^2 \mathcal{P}_k(\vec{x}_{\text{reco}}) + \sum_{i<j} \left(\frac{2\theta_i\theta_j}{\theta_0^2} \right) \mathcal{P}_{ij}(\vec{x}_{\text{reco}})$$

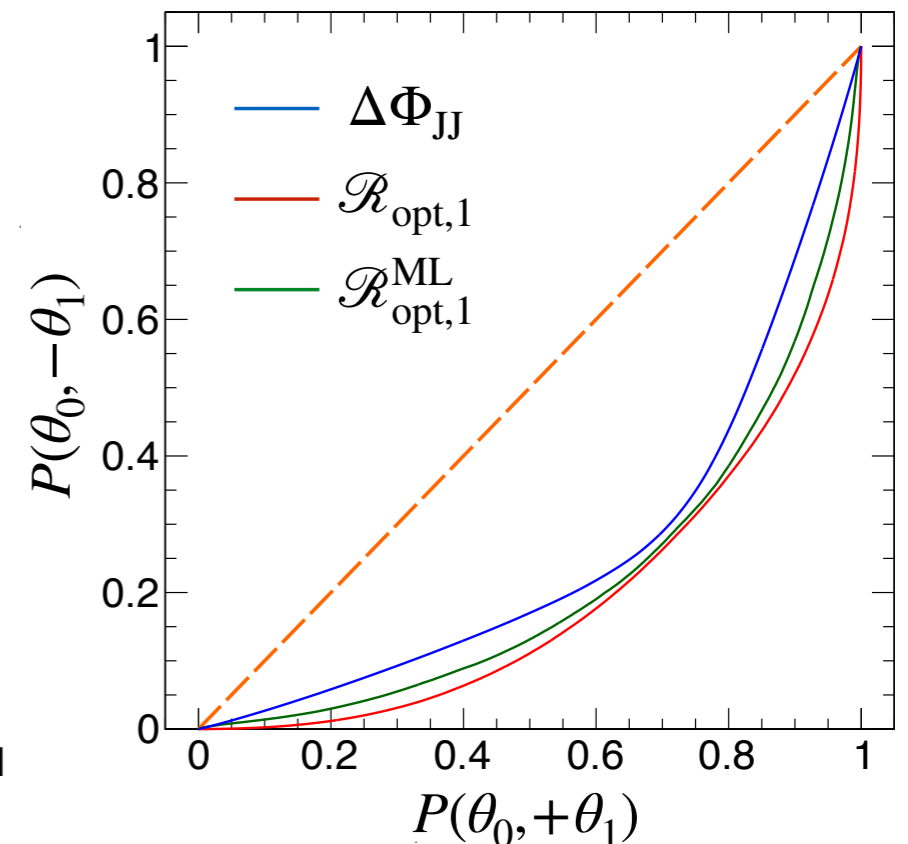
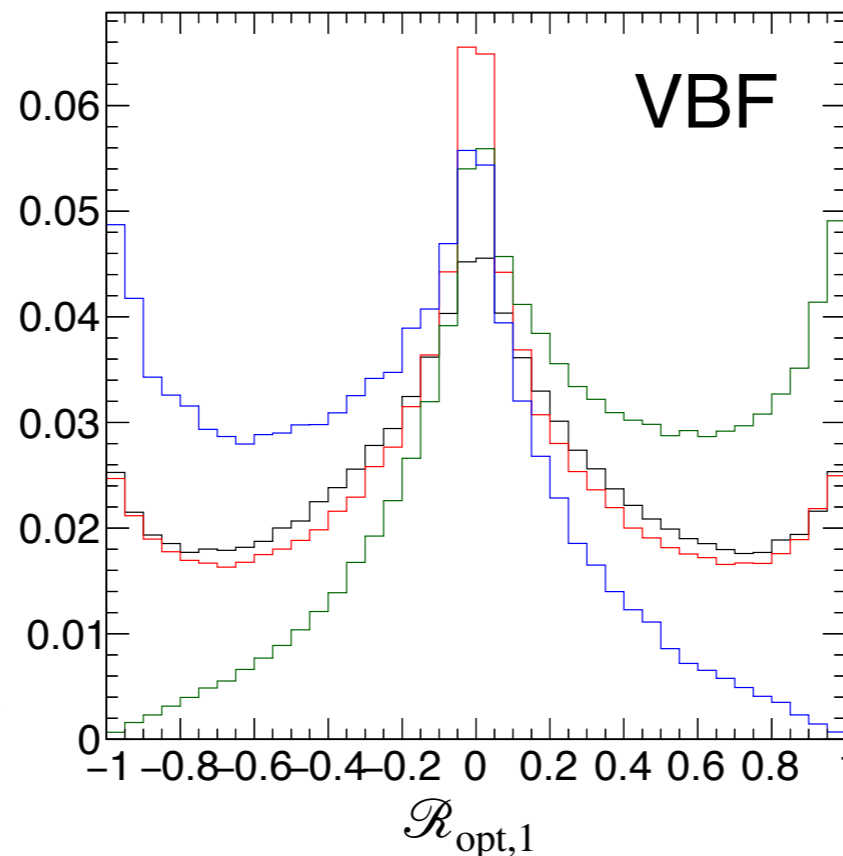
$$\mathcal{R}_{\text{opt},1} = \frac{2\mathcal{P}_{01}(\vec{x}_{\text{reco}}^{\text{full}})}{\mathcal{P}_0(\vec{x}_{\text{reco}}^{\text{full}}) + c \cdot \mathcal{P}_1(\vec{x}_{\text{reco}}^{\text{full}})}$$

\mathcal{P}_{01} matrix element for interference θ_0, θ_1

- **Type-1 Optional Observable** with Matrix Elements:
 - no “classical” analogy
 - in EFT: **SM term** vs. **interference** (linear) term

$$c = 0 \text{ or } \mathcal{R}_{\text{opt},1} \text{ \& \ } \mathcal{R}_{\text{opt},2}$$

- ML equivalent:
train against 2 samples
+mix vs **-mix**
(SM \pm interference θ_0, θ_1)
(no quadratic term for $c = 0$)



e.g. in VBF: $\theta_1 = \tilde{c}_{zz}$

Question from Organizers: ML or ME?

- When to use OO with ML:
 - account for **parton shower**, strong **reconstruction effects**, **missing particles**
 - account for **permutations of particles** (combinatorics)
 - when **ME not available** (readily)
- When to use OO with ME: when all of the above is **not a problem**
- Optimal Observable with ML:
 - trained on simulation based on ME
 - guided by Matrix Element Approach

pair $(\mathcal{R}_{\text{opt},1}, \mathcal{R}_{\text{opt},2})$
 guaranteed to be optimal
 for any size of 1 coupling

(a) use full information as input ! $(\vec{x}_{\text{reco}}^{\text{full}})$

(b) follow ME prescription in training

$$\left\{ \begin{array}{l} \mathcal{R}_{\text{opt},2} = \frac{\mathcal{P}_1(\vec{x}_{\text{reco}}^{\text{full}})}{\mathcal{P}_0(\vec{x}_{\text{reco}}^{\text{full}}) + c \cdot \mathcal{P}_1(\vec{x}_{\text{reco}}^{\text{full}})} \\ \mathcal{R}_{\text{opt},1} = \frac{2\mathcal{P}_{01}(\vec{x}_{\text{reco}}^{\text{full}})}{\mathcal{P}_0(\vec{x}_{\text{reco}}^{\text{full}}) + c \cdot \mathcal{P}_1(\vec{x}_{\text{reco}}^{\text{full}})} \end{array} \right.$$

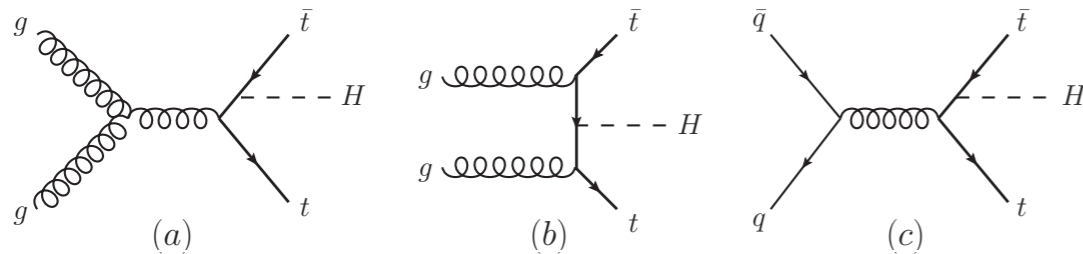
$(0 \leq c \leq 1)$

$\mathcal{R}_{\text{opt},2}^{\text{ML}} \rightarrow$ train 100 % state \mathcal{O} against **SM**

$\mathcal{R}_{\text{opt},1}^{\text{ML}} \rightarrow$ train 50 % state \mathcal{O}/SM against –50 %
 ($c = 1$, remove quadratic term for $c = 0$)

Using Optimized Observables with ML

- When to use OO with ML:



CMS [arXiv:2003.10866](https://arxiv.org/abs/2003.10866)

- first CP analysis in $t\bar{t}H$ process

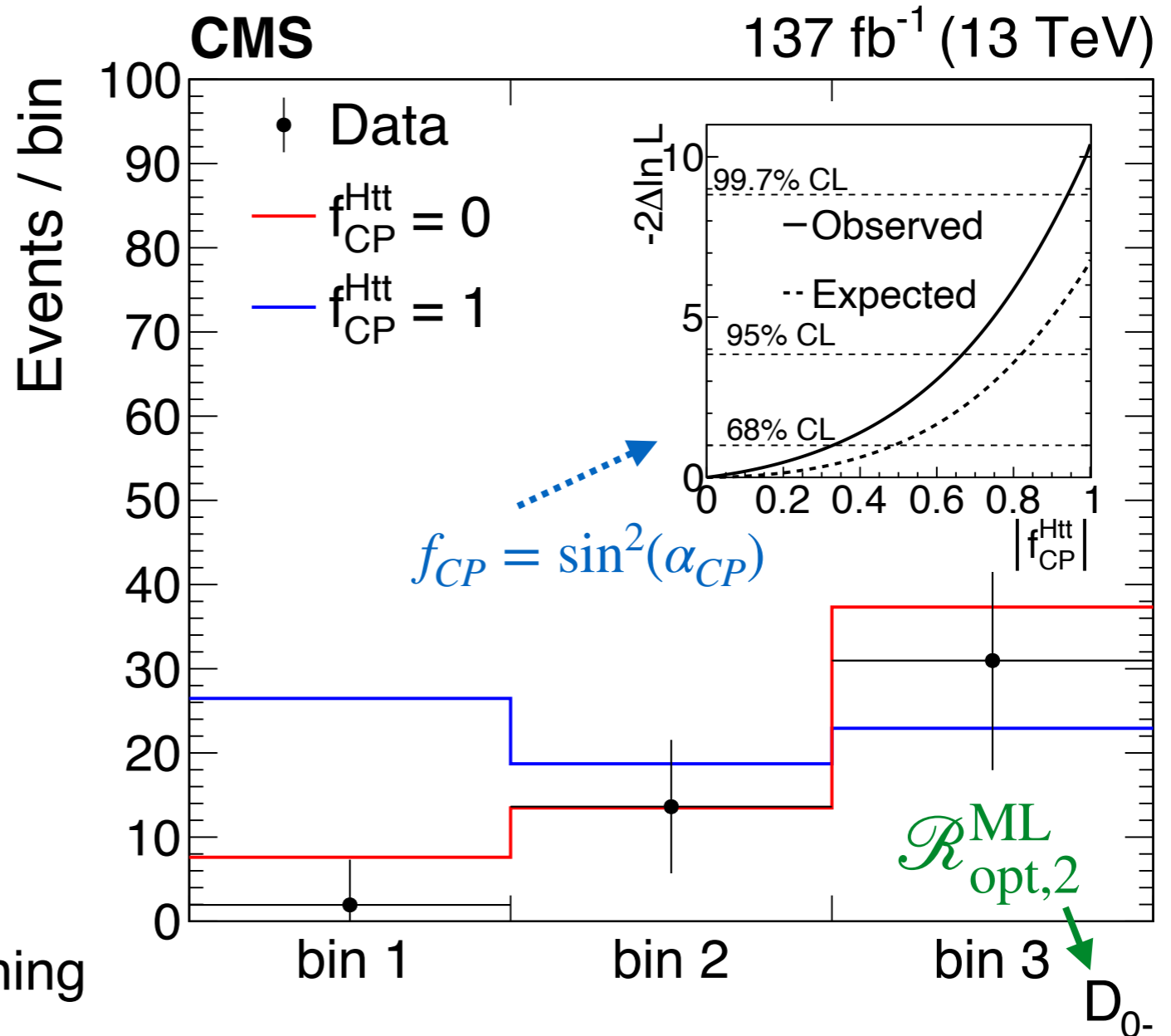
even though feasibility was done with MELA

[arXiv:1606.03107](https://arxiv.org/abs/1606.03107)

- permutation of particles
- lost particles motivated ML

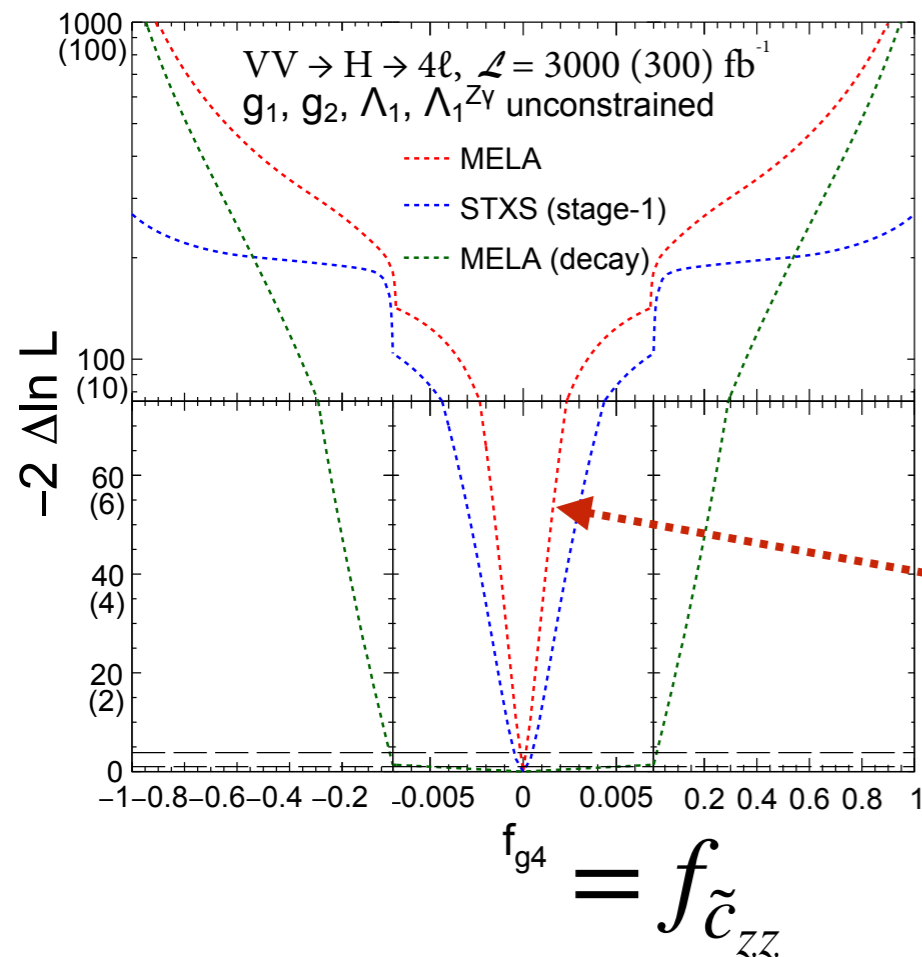
(a) used full information as input !

(b) followed ME prescription in training



Using Optimized Observables with MELA

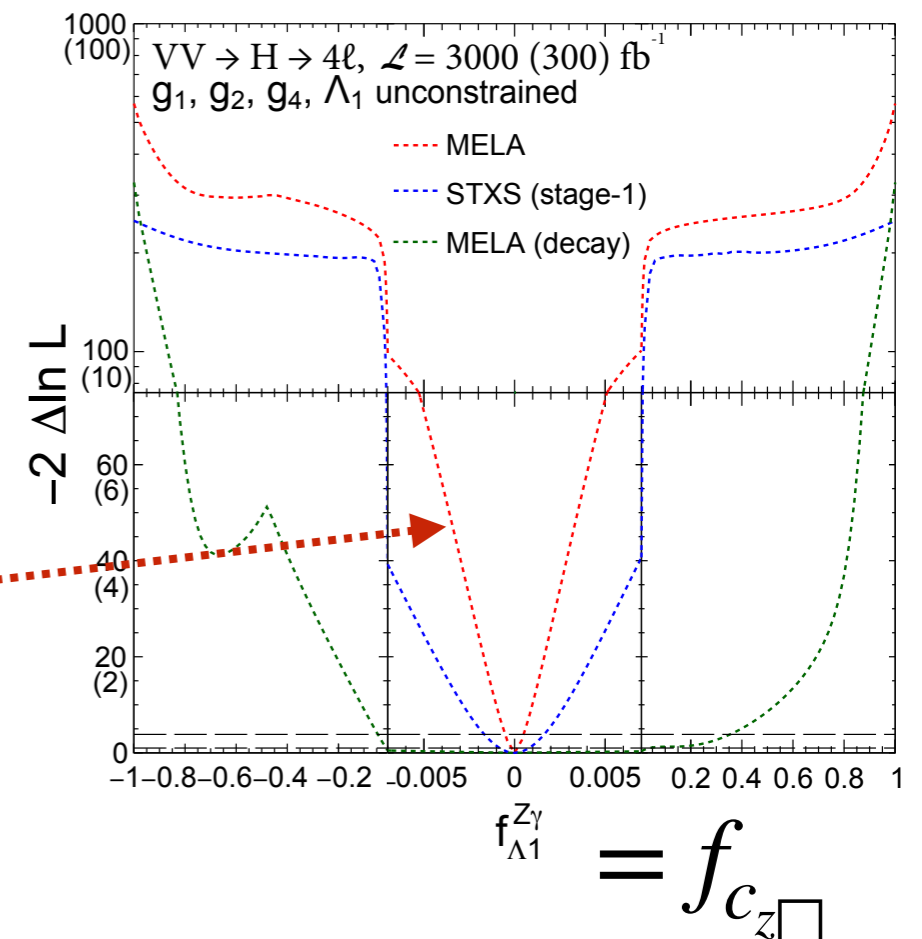
- MELA (Matrix Element Likelihood Approach) — [tutorial yesterday](#) by Mohit Srivastav
- Example process $VV \rightarrow H \rightarrow 4\ell$
 - all production mechanisms: $ggH, VBF, VH, t\bar{t}H, tH, b\bar{b}H$
 - three approaches to binning: **dedicated**, **decay-only**, **STXS v1.1**
 - 5 HVV , 2 Hgg , 2 Htt couplings free \Rightarrow Optimal Observables targeting each



× 2 – 3 tighter constraints
 with **Optimal MELA**
 vs **Differential STXS**

production information
 $VV \rightarrow H$

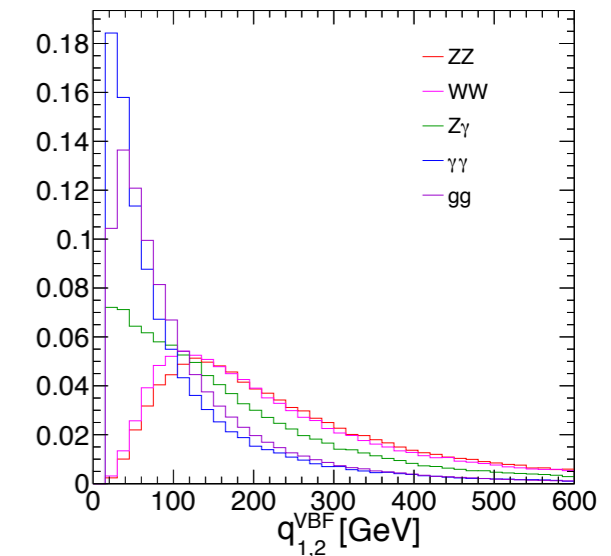
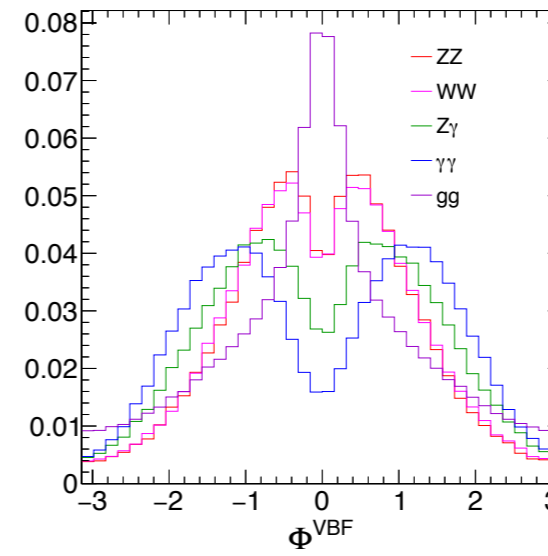
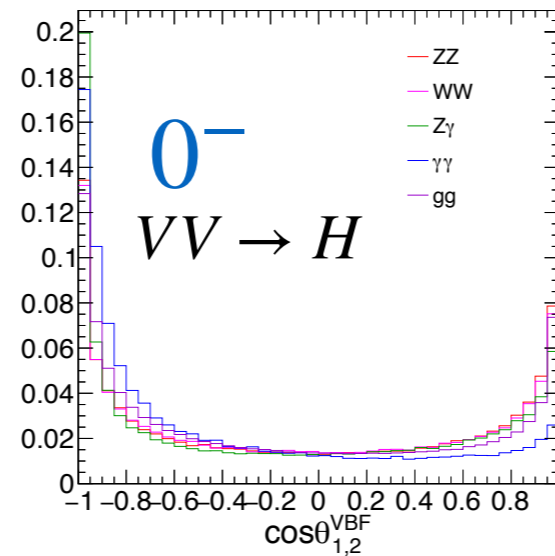
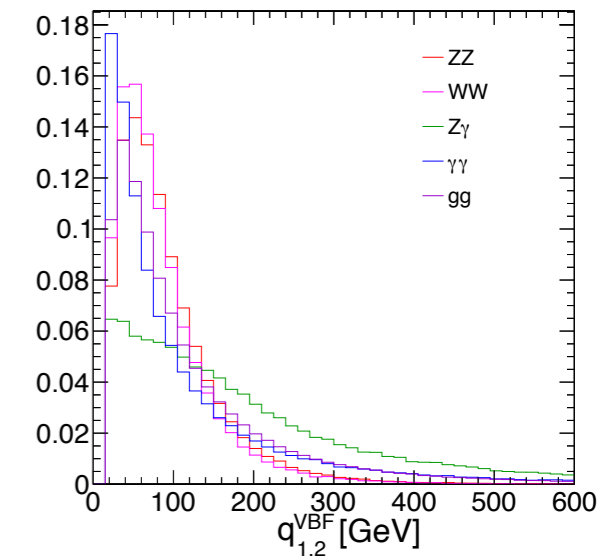
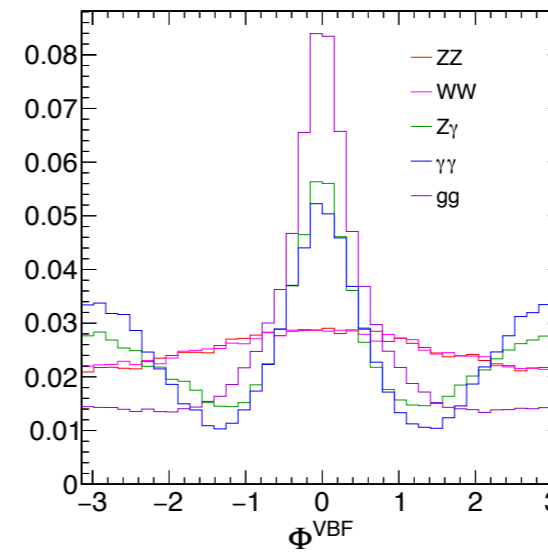
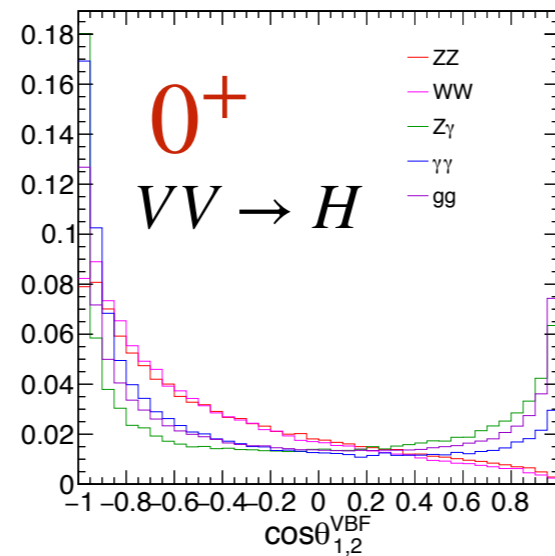
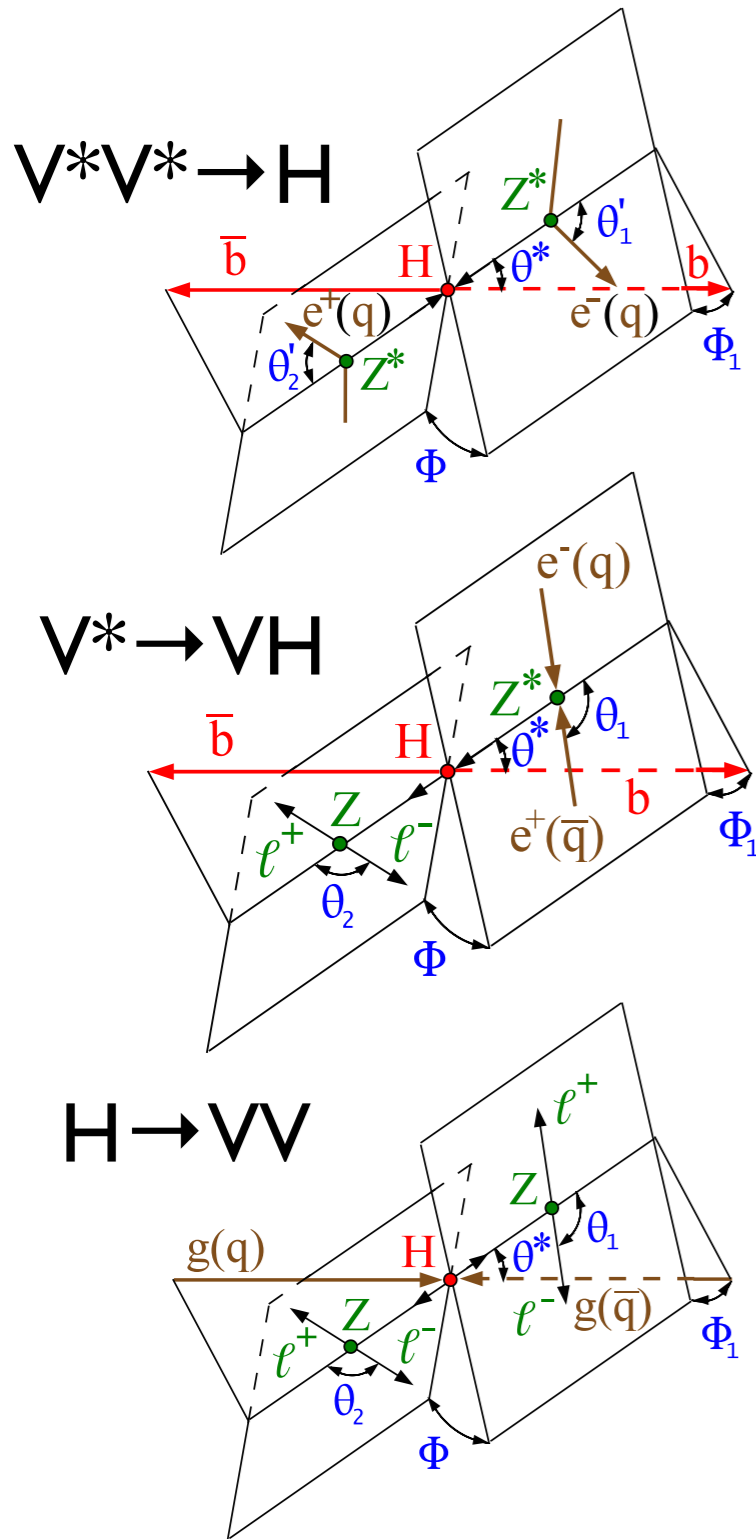
[arXiv:2002.09888](https://arxiv.org/abs/2002.09888)



Using Optimized Observables with MELA

- Take VBF topology \Rightarrow $HWW, HZZ, HZ\gamma, H\gamma\gamma, Hgg$ couplings

— unique multi-D. kinematics in each case:
(want to use it all to isolate each operator)



hep-ph [arXiv:2002.09888](https://arxiv.org/abs/2002.09888)

use [JHUGen/MELA](https://github.com/JHU-HEP/JHUGen) in this study, but ideas are generic

Question from Organizers:

- How >1 observables can be selected and designed to better constrain coefficients?
- Ideally **1** or **2 observables** per target operator, if **distinct** and **important** enough

— up to **7 observables** use in [CMS-HIG-19-009](#)

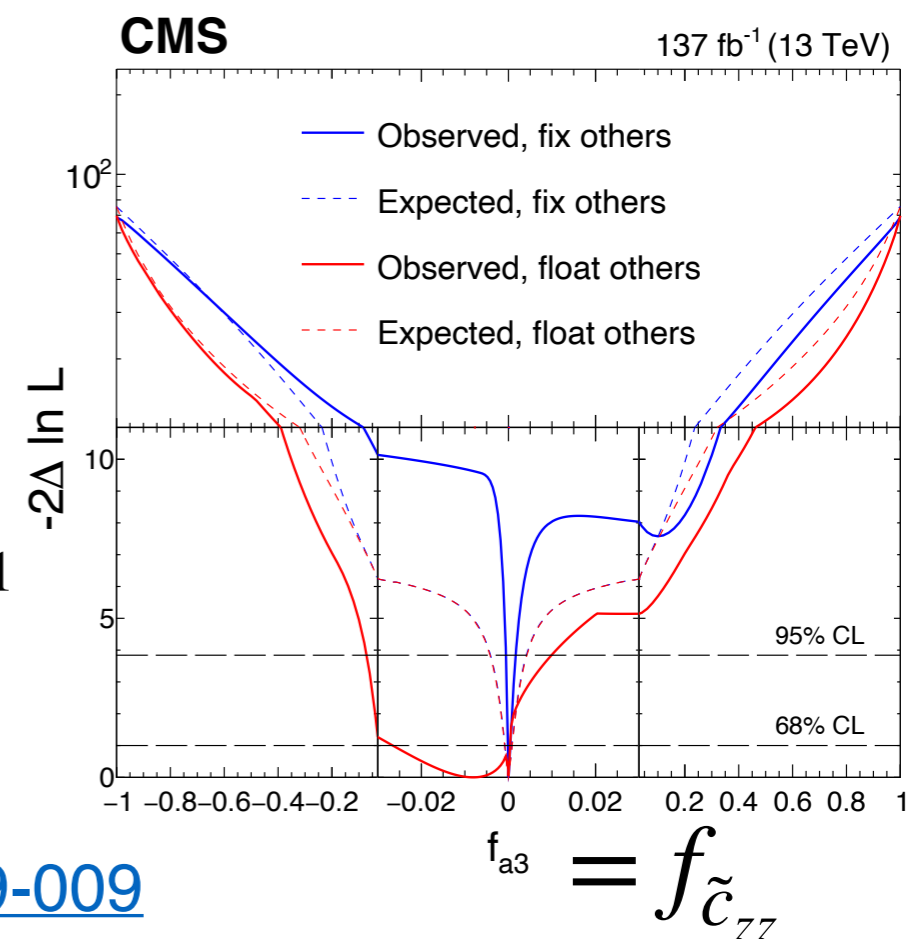
depending on category (targeting a process):

1 to suppress background

2 pairs ($\mathcal{R}_{\text{opt},1}, \mathcal{R}_{\text{opt},2}$) for c_{zz}, \tilde{c}_{zz}

2 of $\mathcal{R}_{\text{opt},2}$ for $\delta c_z, c_{z\Box}$ due to correlation to $\mathcal{R}_{\text{opt},1}$

used OO of both types due to limited sensitivity



[CMS-HIG-19-009](#)

Boosted	$p_T^{4\ell} > 120 \text{ GeV}$	$\mathcal{D}_{\text{bkg}}, p_T^{4\ell}$
VBF-1jet	$\mathcal{D}_{1\text{jet}}^{\text{VBF}} > 0.7$	$\mathcal{D}_{\text{bkg}}, p_T^{4\ell}$
VBF-2jet	$\mathcal{D}_{2\text{jet}}^{\text{VBF}} > 0.5$	$\mathcal{D}_{\text{bkg}}, \mathcal{D}_{0h+}^{\text{VBF+dec}}, \mathcal{D}_{0-}^{\text{VBF+dec}}, \mathcal{D}_{\Lambda 1}^{\text{VBF+dec}}, \mathcal{D}_{\Lambda 1}^{\text{Z}\gamma, \text{VBF+dec}}, \mathcal{D}_{\text{int}}^{\text{VBF}}, \mathcal{D}_{\text{CP}}^{\text{VBF}}$
VH-hadronic	$\mathcal{D}_{2\text{jet}}^{\text{VH}} > 0.5$	$\mathcal{D}_{\text{bkg}}, \mathcal{D}_{0h+}^{\text{VH+dec}}, \mathcal{D}_{0-}^{\text{VH+dec}}, \mathcal{D}_{\Lambda 1}^{\text{VH+dec}}, \mathcal{D}_{\Lambda 1}^{\text{Z}\gamma, \text{VH+dec}}, \mathcal{D}_{\text{int}}^{\text{VH}}, \mathcal{D}_{\text{CP}}^{\text{VH}}$
VH-leptonic	see Section 3	$\mathcal{D}_{\text{bkg}}, p_T^{4\ell}$
Untagged	none of the above	$\mathcal{D}_{\text{bkg}}, \mathcal{D}_{0h+}^{\text{dec}}, \mathcal{D}_{0-}^{\text{dec}}, \mathcal{D}_{\Lambda 1}^{\text{dec}}, \mathcal{D}_{\Lambda 1}^{\text{Z}\gamma, \text{dec}}, \mathcal{D}_{\text{int}}^{\text{dec}}, \mathcal{D}_{\text{CP}}^{\text{dec}}$

Considerations for Optimized Observables

- We should be able to explore **unique kinematics** in our detectors
 - using **dedicated tools** (ME, MVA, $\Delta\Phi_{JJ}, \dots$) (optimal)
 - using **full detector simulation** of EFT effects (correct)

(1) Challenges in **number of terms** \Rightarrow **bookkeeping, re-weighting** ([MELA](#))

(2) Challenges in **number of observables** \Rightarrow optimize bins

- often keep quadratic terms: to have positive probability
- may keep optimal Observable type-2: when sensitivity still limited

$$\mathcal{P}(\vec{x}; \vec{f}) = \sum_{k \leq l \leq m \leq n=1}^K \mathcal{P}_{klmn}(\vec{x}) \sqrt{|f_k \cdot f_l \cdot f_m \cdot f_n|} \text{sign}(f_k \cdot f_l \cdot f_m \cdot f_n)$$

K - number of couplings, N - number of products (4 in $VV \rightarrow H \rightarrow VV$, 2 in $gg \rightarrow H$)

$$\text{total \# terms} = \frac{(N + K - 1)!}{N!(K - 1)!} = \begin{array}{l} 3 \text{ for } N=2, K=2 \text{ in } gg \rightarrow H, ttH \\ 15 \text{ for } N=2, K=5 \text{ in decay } H \rightarrow VV \rightarrow 4\ell \\ 70 \text{ for } N=4, K=5 \text{ in } VV \rightarrow H \rightarrow VV \\ 495 \text{ for } N=4, K=9 \text{ in } VV \rightarrow H \rightarrow VV \text{ (offshell+bkg)} \end{array}$$

$$\text{\# linear terms} = K$$

Considerations for Optimized Observables

- With the large number of Operators, e.g. in VBS / VBF / VH / H→VV:

$$\begin{array}{lll}
 C^{\varphi W}, C^{\varphi B}, C^{\varphi WB} & \leftrightarrow & c_{zz}, c_{z\gamma}, c_{\gamma\gamma} & K_t, \tilde{K}_t, K_b, \tilde{K}_b \\
 C^{\varphi \tilde{W}}, C^{\varphi \tilde{B}}, C^{\varphi \tilde{W}B} & \leftrightarrow & \tilde{c}_{zz}, \tilde{c}_{z\gamma}, \tilde{c}_{\gamma\gamma} & \\
 C^{\varphi D}, C^{\varphi \square}, \delta v & \leftrightarrow & \delta c_z, \delta c_w, c_{z\square} & C_L^{Ztt}, C_R^{Ztt} \\
 C^{\varphi G}, C^{\varphi \tilde{G}} & = & c_{gg}, \tilde{c}_{gg} & C^W, C^{\tilde{W}}
 \end{array}$$

- Define the target set of EFT operators θ_i is important **in advance**:

- **rotate operators** to remove flat directions

- determine sensitive θ_i e.g. $C^{\varphi W}, C^{\varphi B}, C^{\varphi WB} \leftrightarrow c_{zz}, c_{z\gamma}, c_{\gamma\gamma}$

- Cannot keep ~20 optimal Observables

- define **optimal Observables** for a limited set of **operators** for a given **process**

- sometimes using direct **angular** and q^2 information (~full) is optimal (recall VH)

Summary

- General considerations: for observables
 - variety of **approaches**, some historical
 - no unique **recommendation**
 - awareness** of pros / cons, tools
 - practical** choices
- Observables for EFT
 - from “**simple**” to **optimized** observables
 - clear prescription if optimization is desired
needed: clear target, choice of operators
- Observables for EFT
 - **full information** — use in MEM, ML
 - **optimized Observables** — in dedicated fits
 - **EFT observables** — in differential / dedicated fits
 - **SM observables** — in differential

