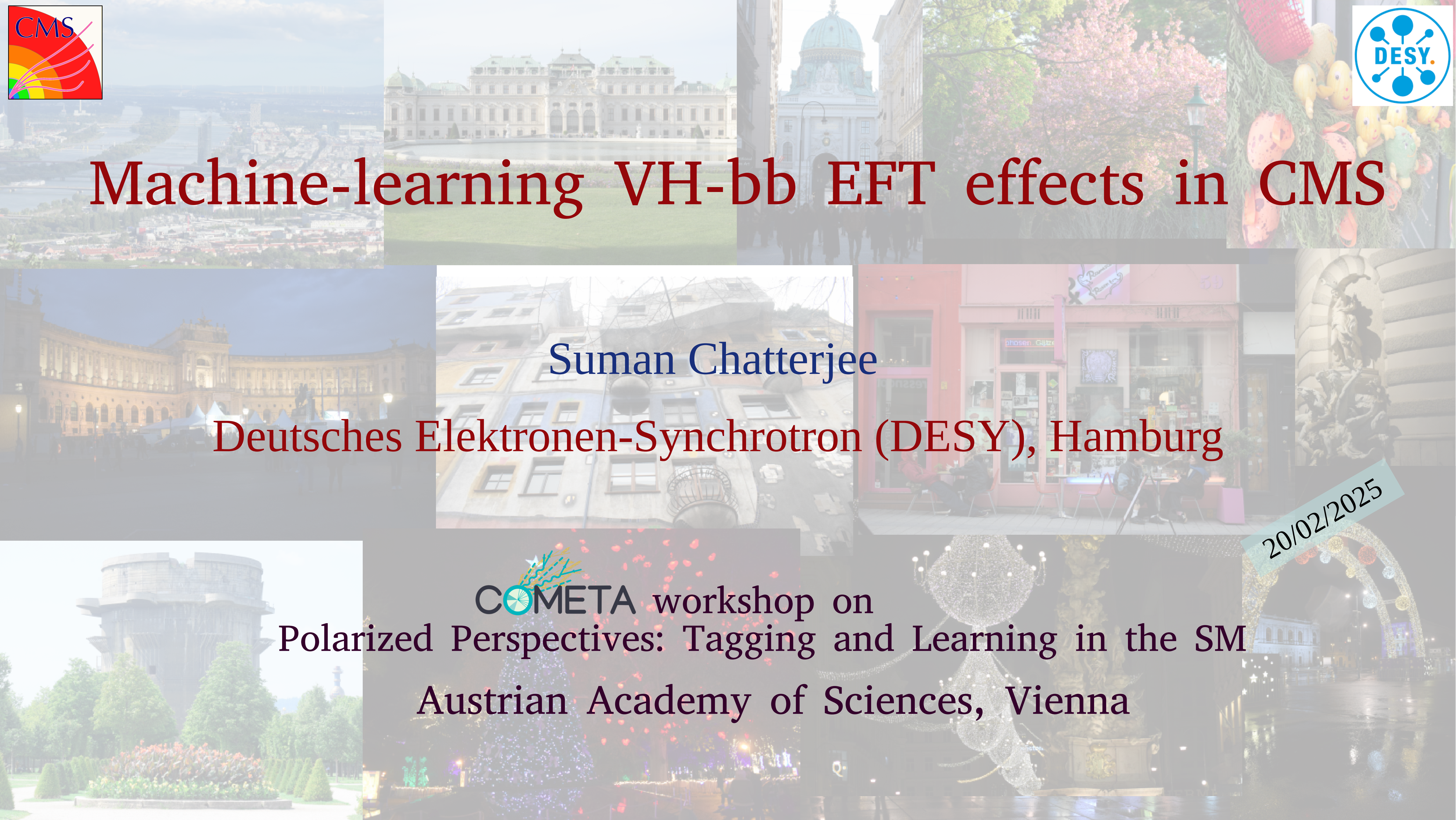


Machine-learning VH-bb EFT effects in CMS

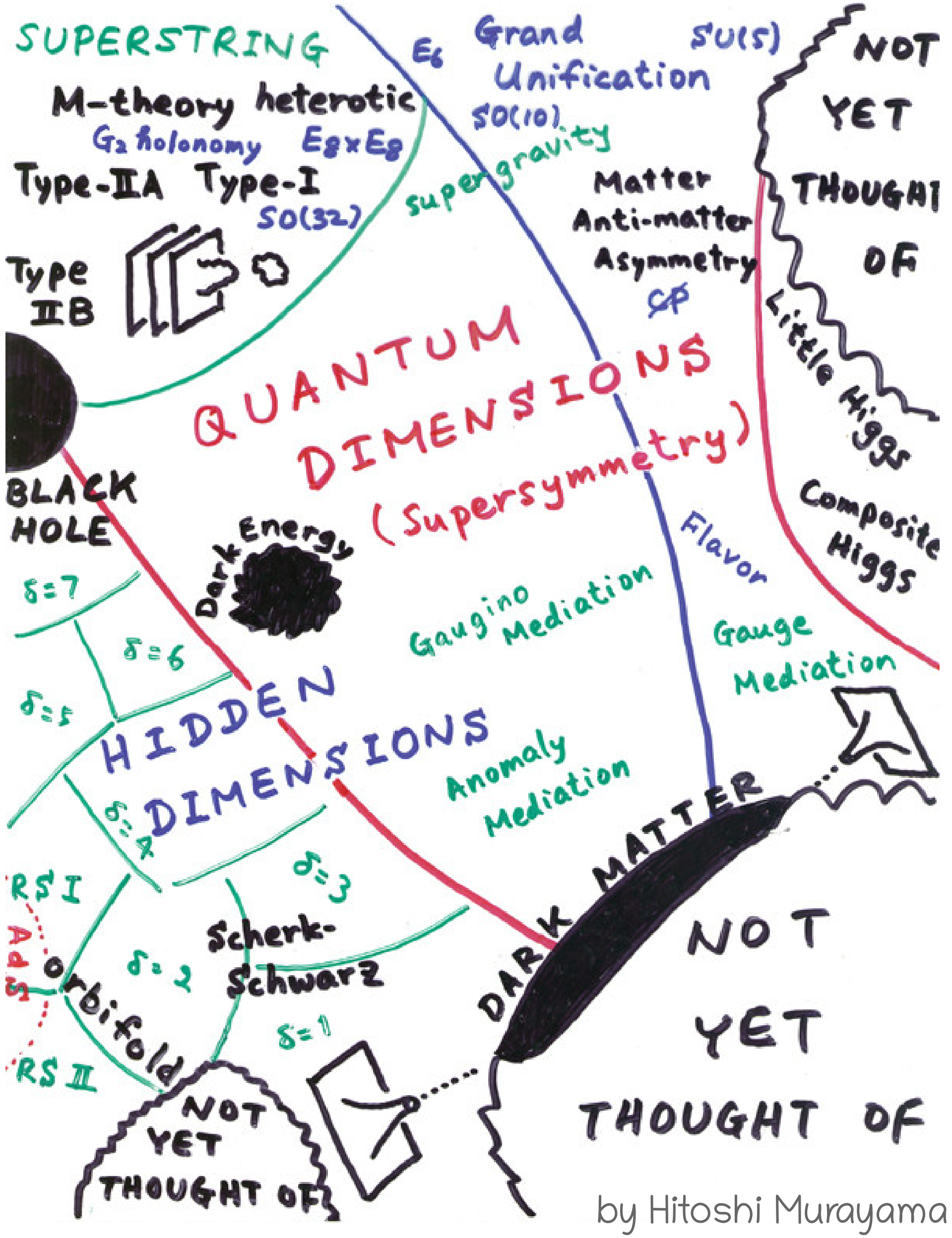
Suman Chatterjee

Deutsches Elektronen-Synchrotron (DESY), Hamburg

20/02/2025

COMETA workshop on
Polarized Perspectives: Tagging and Learning in the SM
Austrian Academy of Sciences, Vienna

Landscape of new physics



by Hitoshi Murayama

[image link]

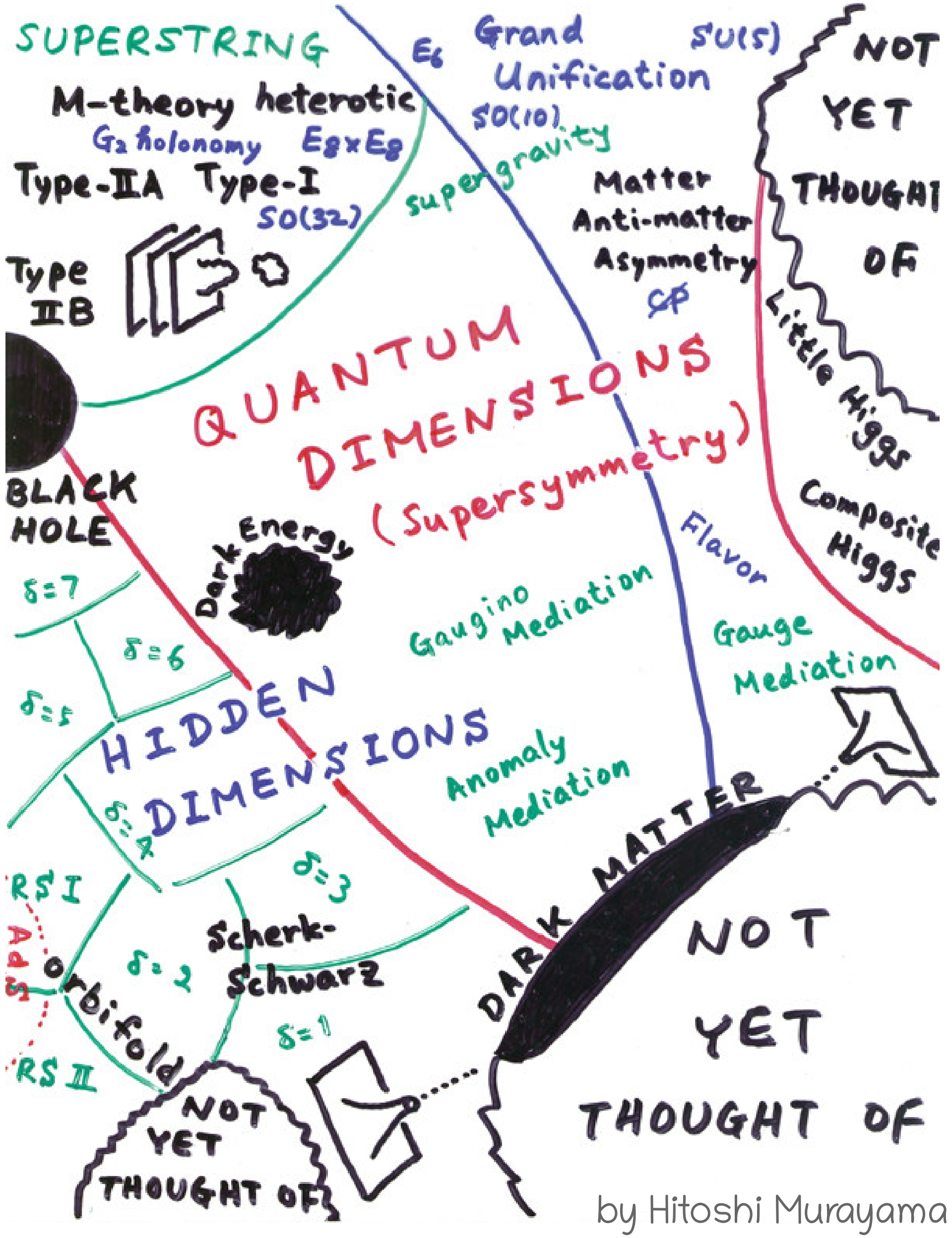
Plethora of new ideas → solving one or many problems

Formulated in terms of Lagrangians

← Parameters: couplings & energy scales

→ Predictions for new phenomena at experiments

Landscape of new physics



by Hitoshi Murayama

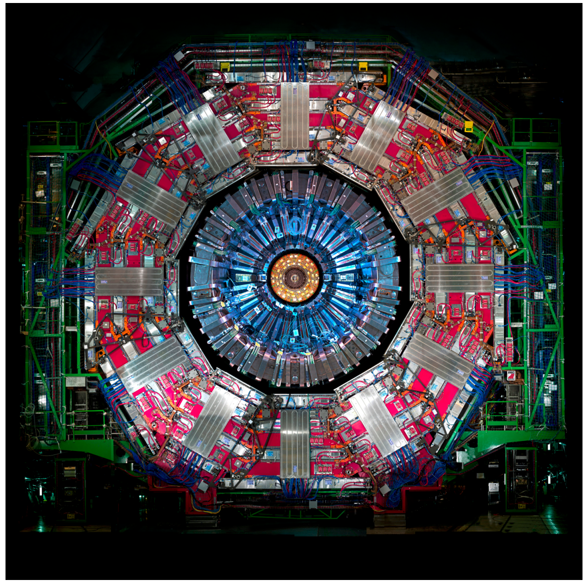
[image link]

Plethora of new ideas → solving one or many problems

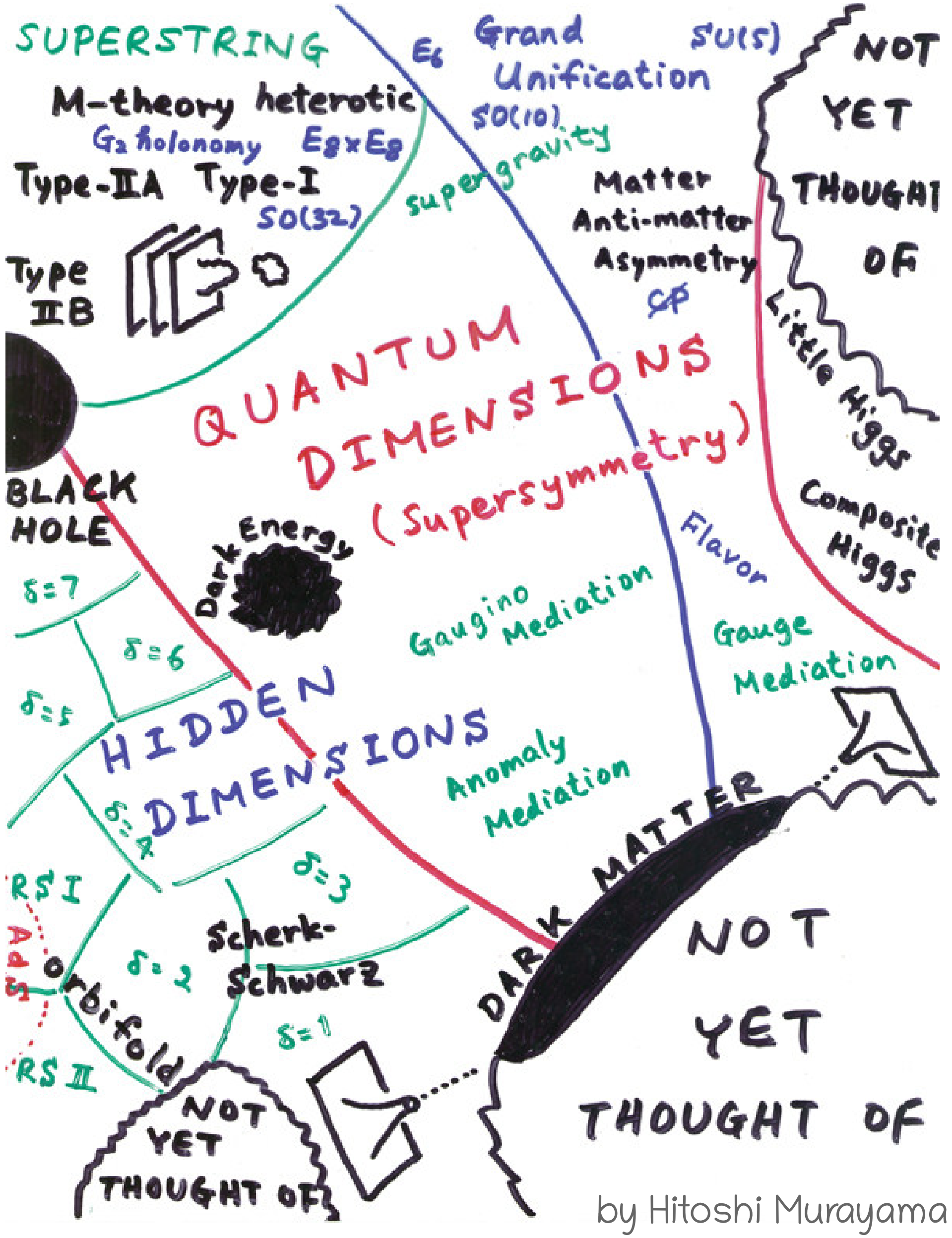
Formulated in terms of Lagrangians

← Parameters: couplings & energy scales

→ Predictions for new phenomena at experiments



Landscape of new physics



by Hitoshi Murayama

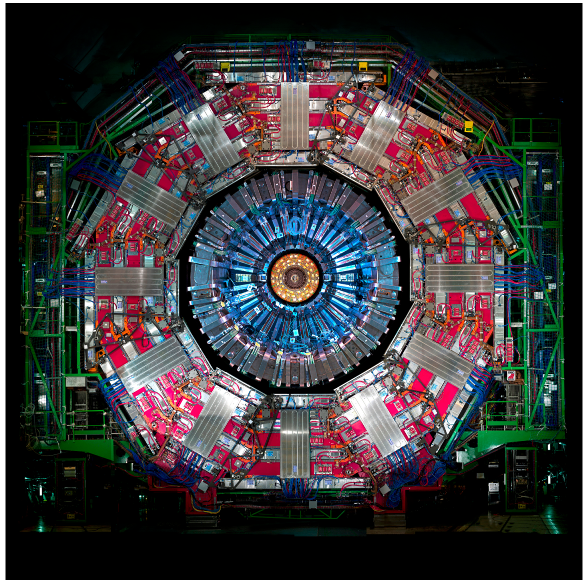
[image link]

Plethora of new ideas → solving one or many problems

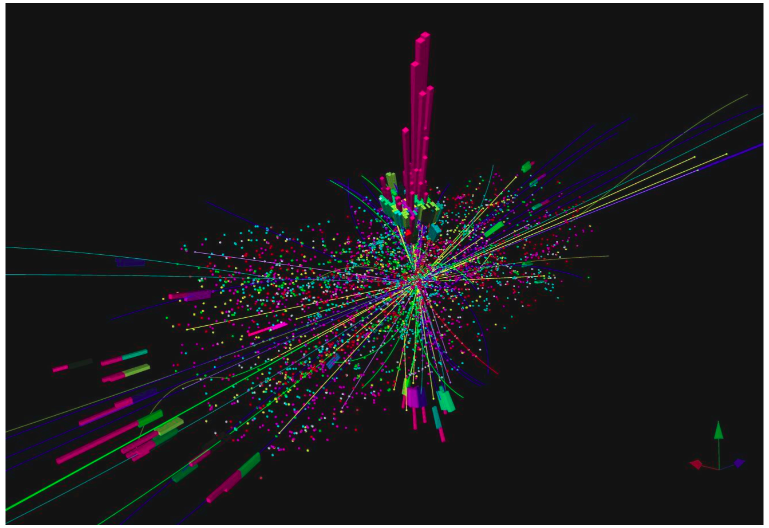
Formulated in terms of Lagrangians

← Parameters: couplings & energy scales

→ Predictions for new phenomena at experiments



Hidden Valley Z' → jets (simulation)



[image link]

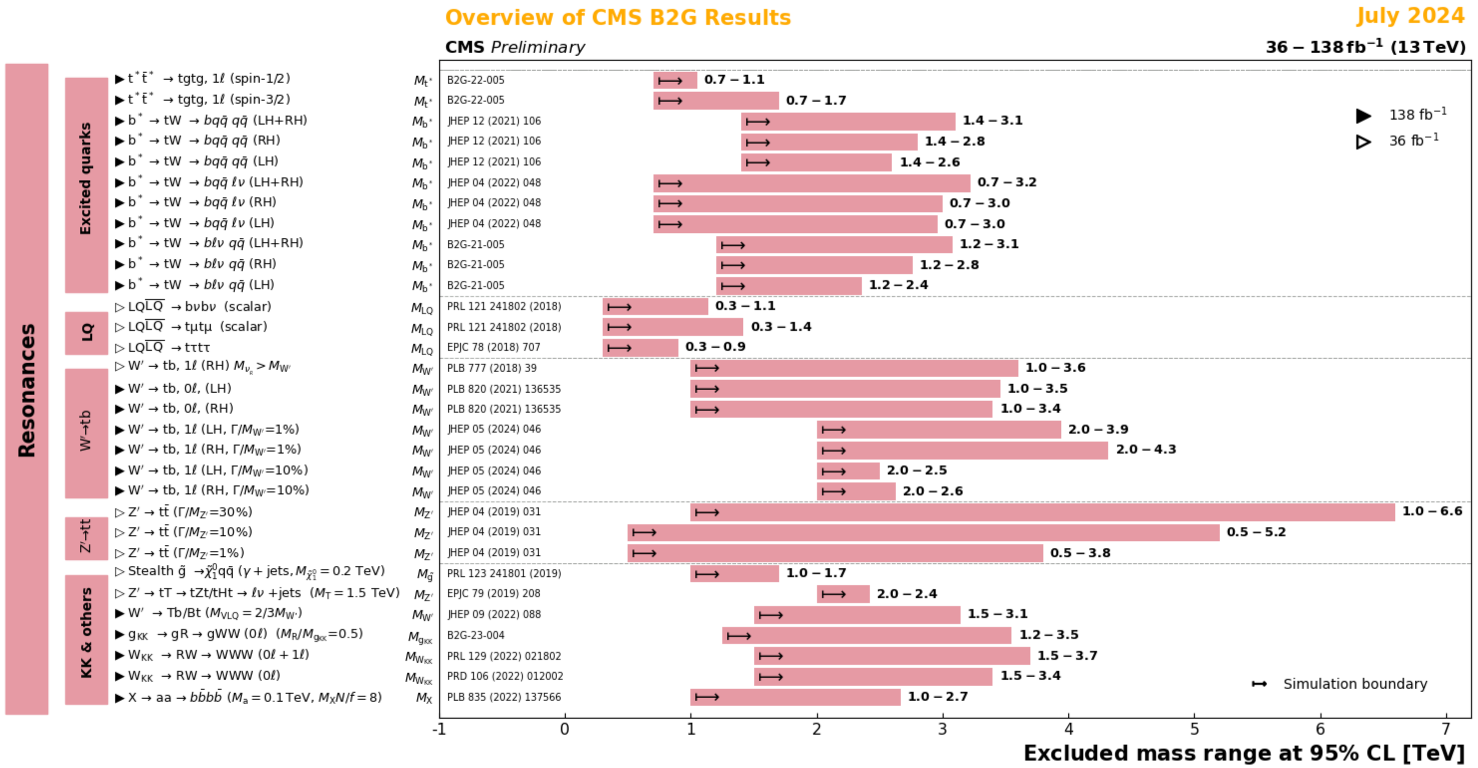
Scale of new physics?

Newest fundamental particle discovered: Last missing piece in standard model (SM)

Scale of new physics?

Newest fundamental particle discovered: Last missing piece in standard model (SM)

CMS B2G-Resonances summary plots



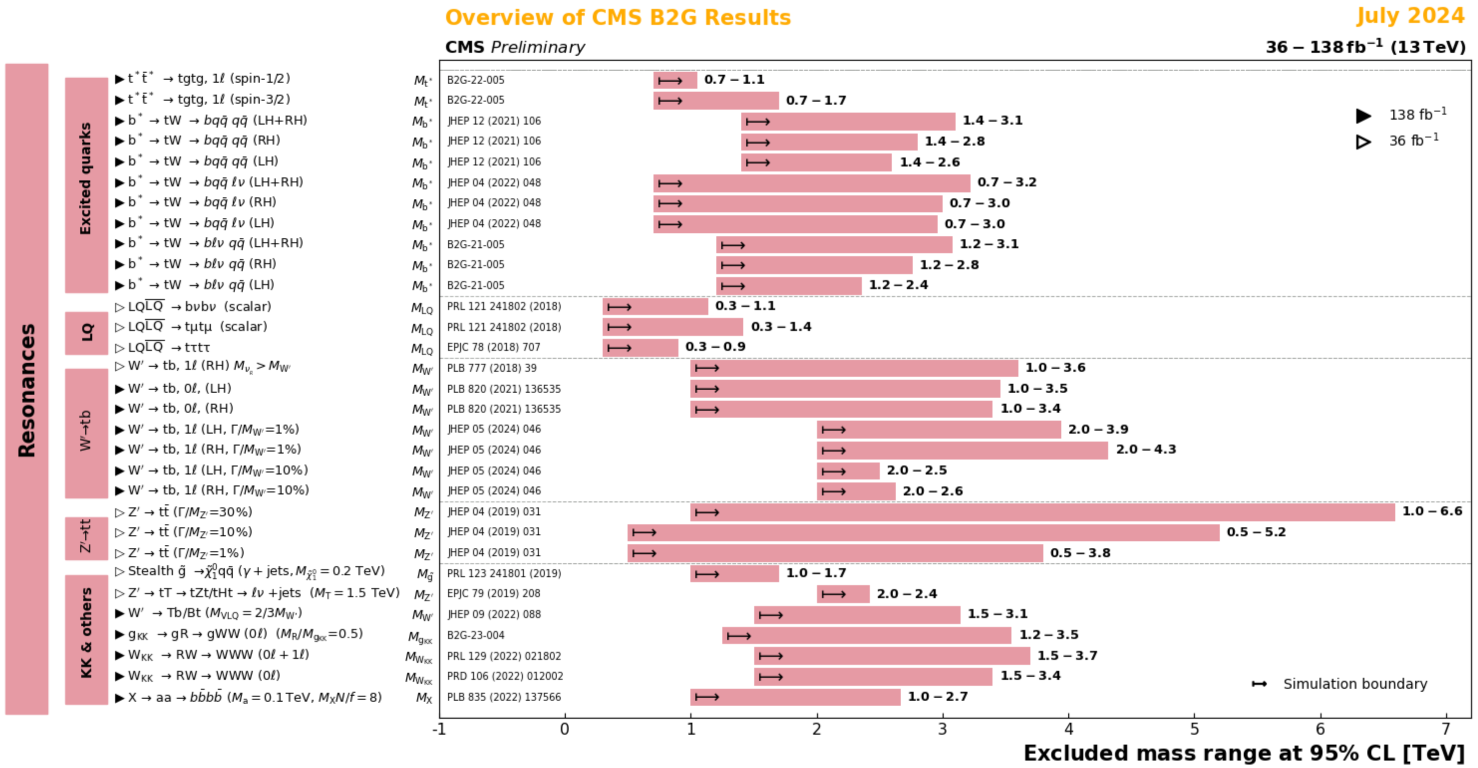
No smoking gun signature of a heavy resonance yet from LHC data

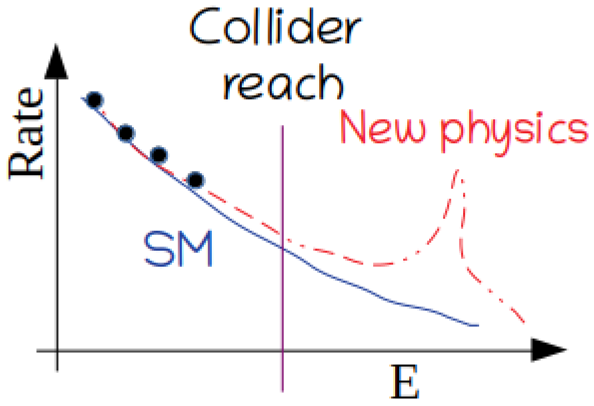
→ Hint for a separation of new physics scale & electroweak scale?

Scale of new physics?

Newest fundamental particle discovered: Last missing piece in standard model (SM)

CMS B2G-Resonances summary plots





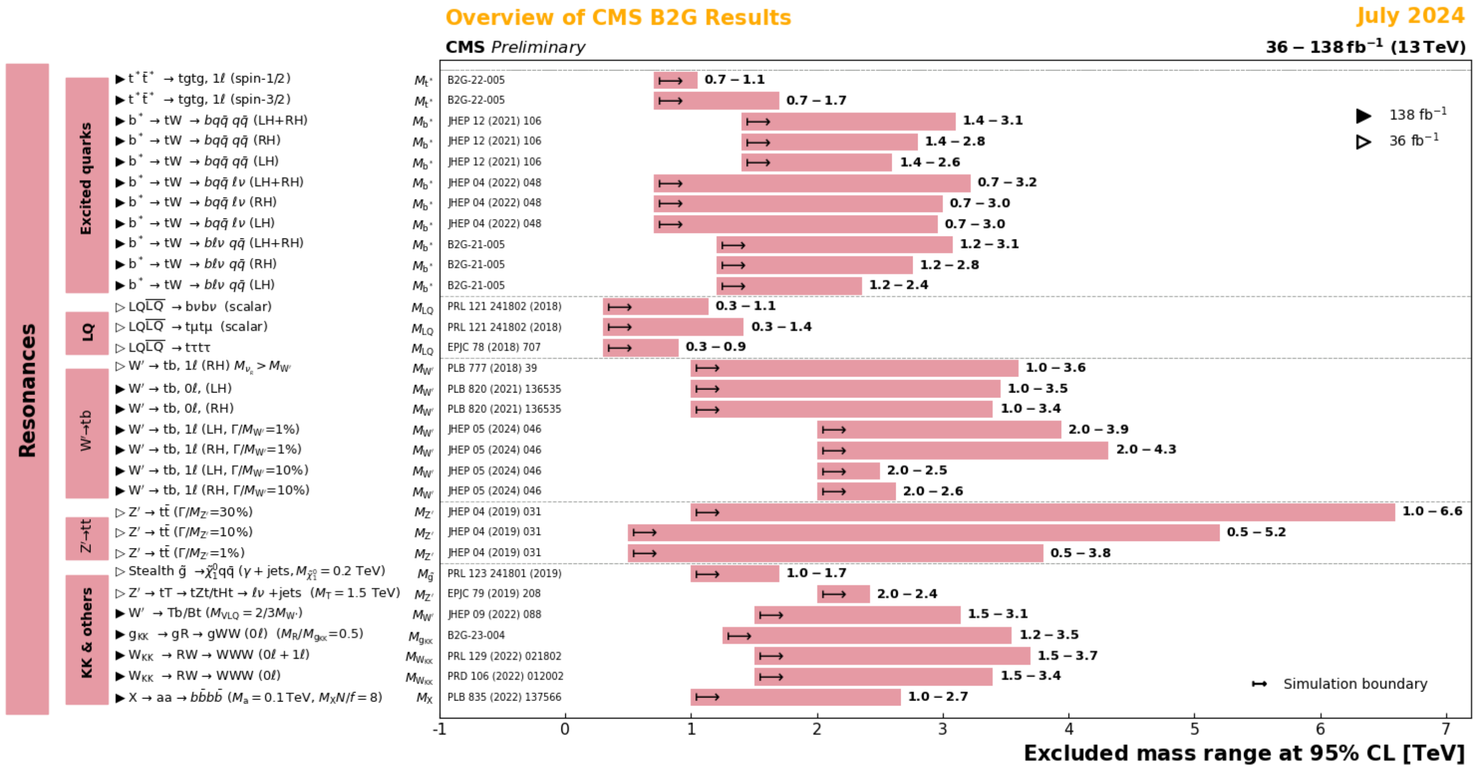
No smoking gun signature of a heavy resonance yet from LHC data

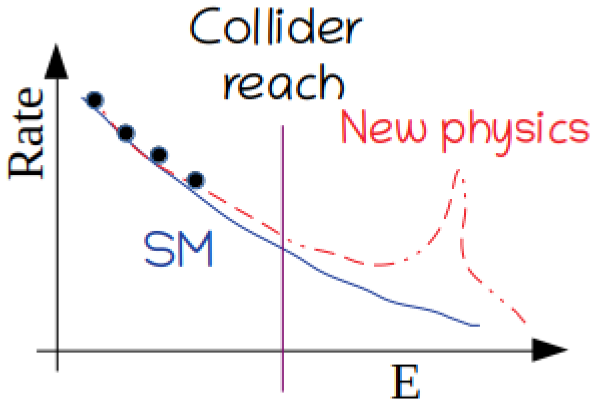
→ Hint for a separation of new physics scale & electroweak scale?

Scale of new physics?

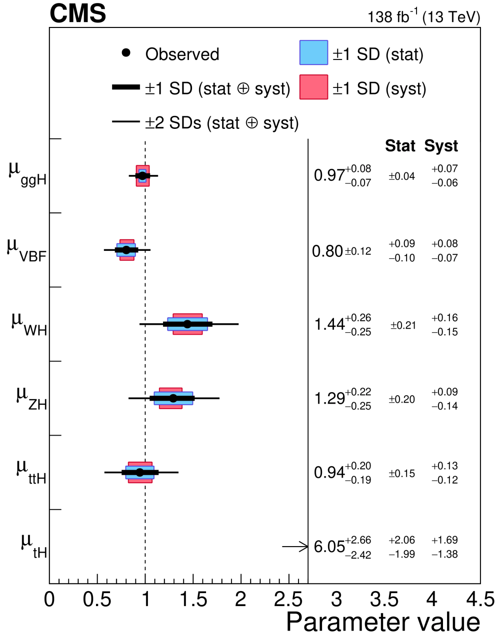
Newest fundamental particle discovered: Last missing piece in standard model (SM)

CMS B2G-Resonances summary plots





Nature 607 (2022) 60-68



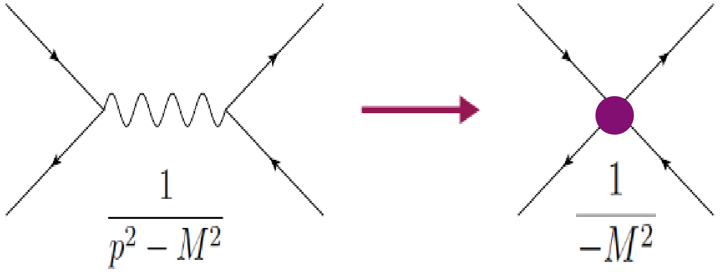
No smoking gun signature of a heavy resonance yet from LHC data

→ Hint for a separation of new physics scale & electroweak scale?

Large new physics scale
consistent with inclusive measurements

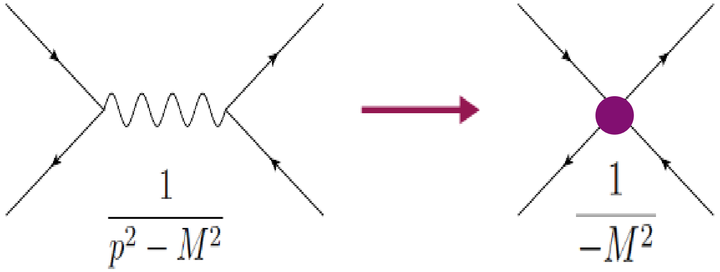
Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions



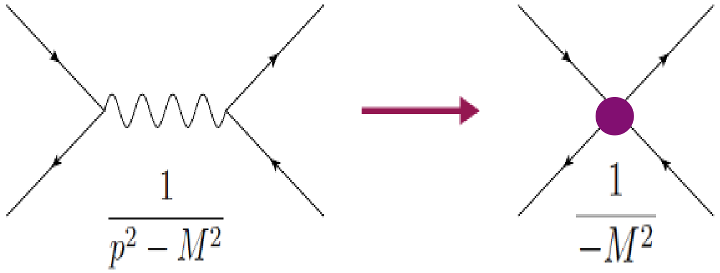
Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions



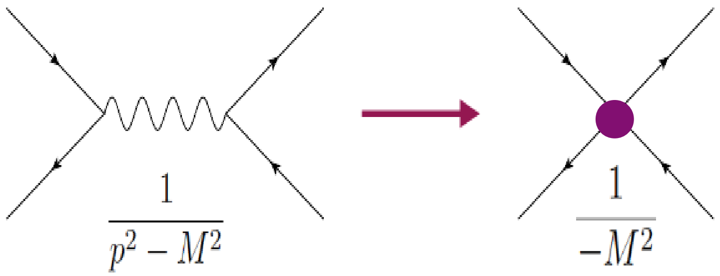
Standard model effective field theory (SMEFT)

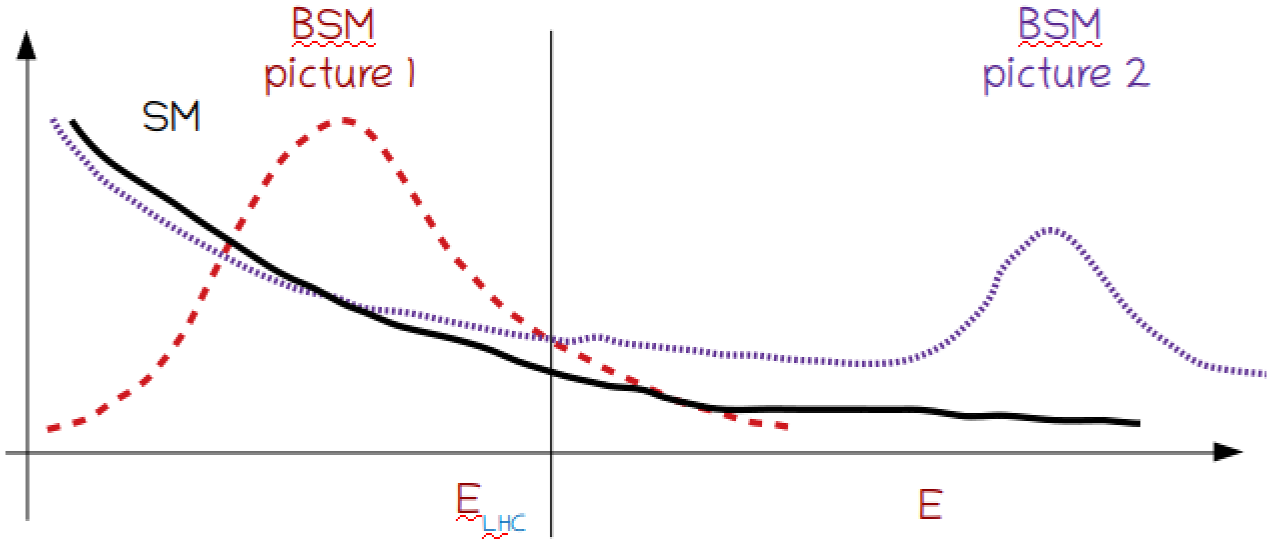
New (heavy) particles modify SM interactions



Standard model effective field theory (SMEFT)

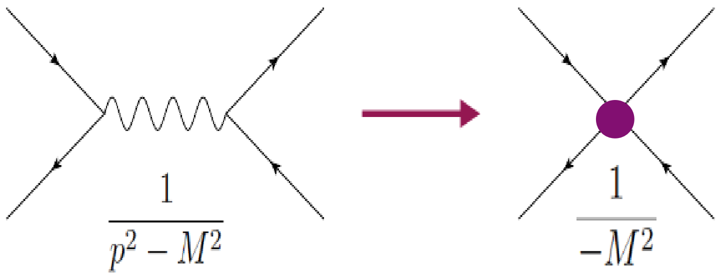
New (heavy) particles modify SM interactions



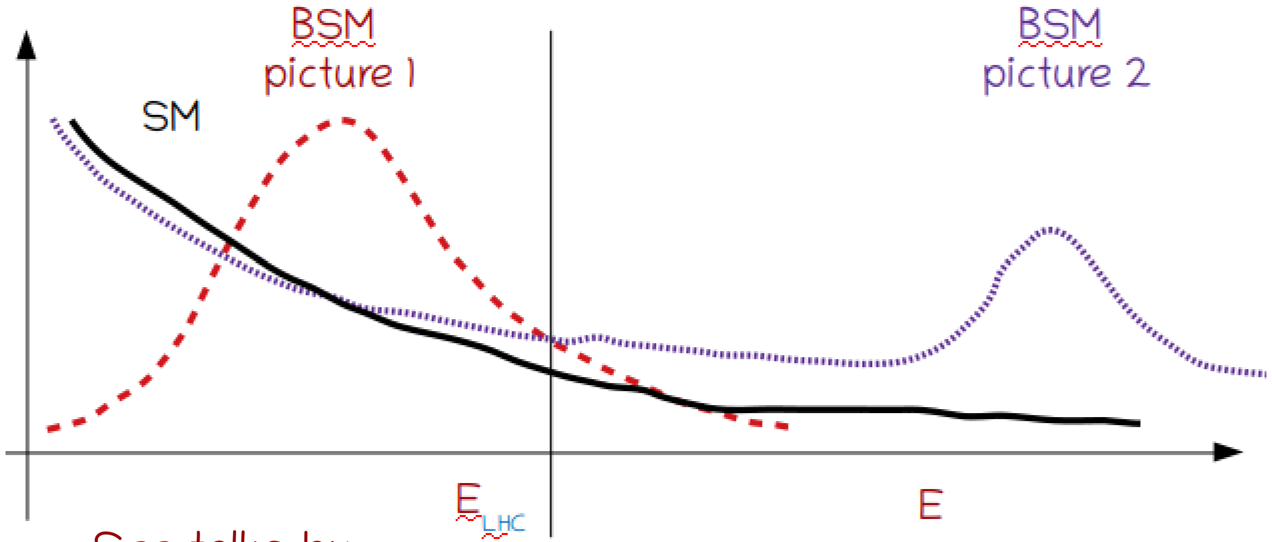


Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions



$$\frac{1}{p^2 - M^2} \rightarrow \frac{1}{-M^2}$$



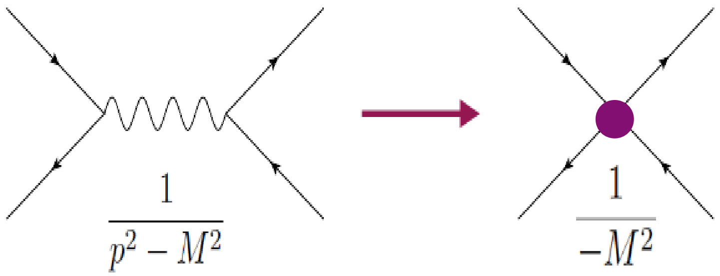
See talks by

A. Malara

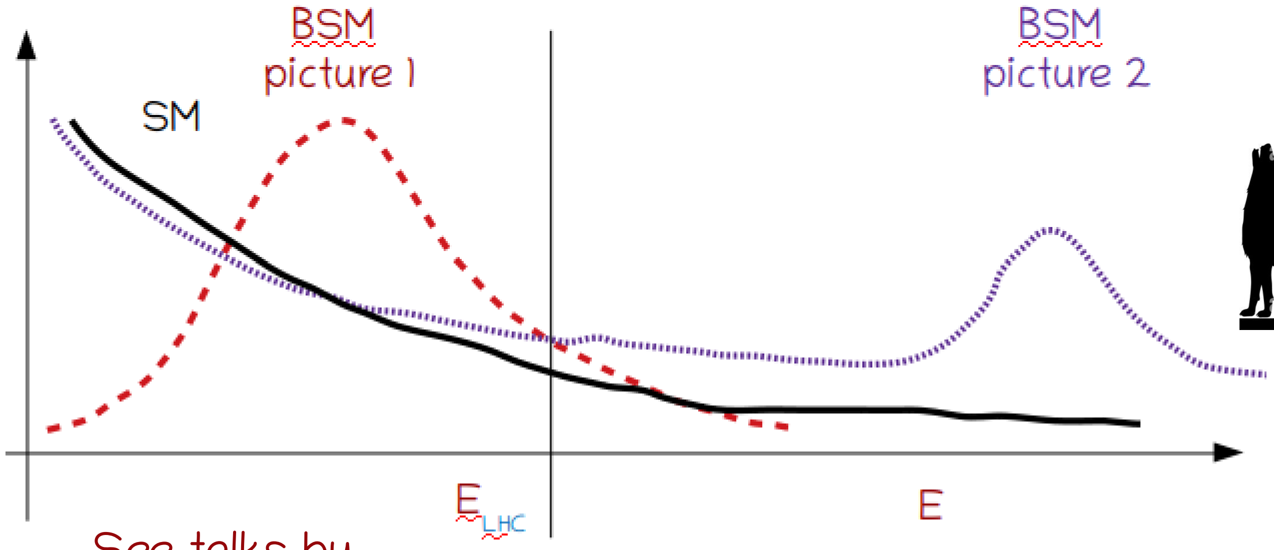
A. Agapitos

Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions



$$\frac{1}{p^2 - M^2} \longrightarrow \frac{1}{-M^2}$$



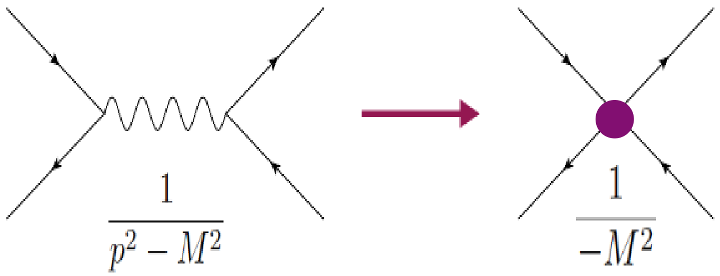
See talks by

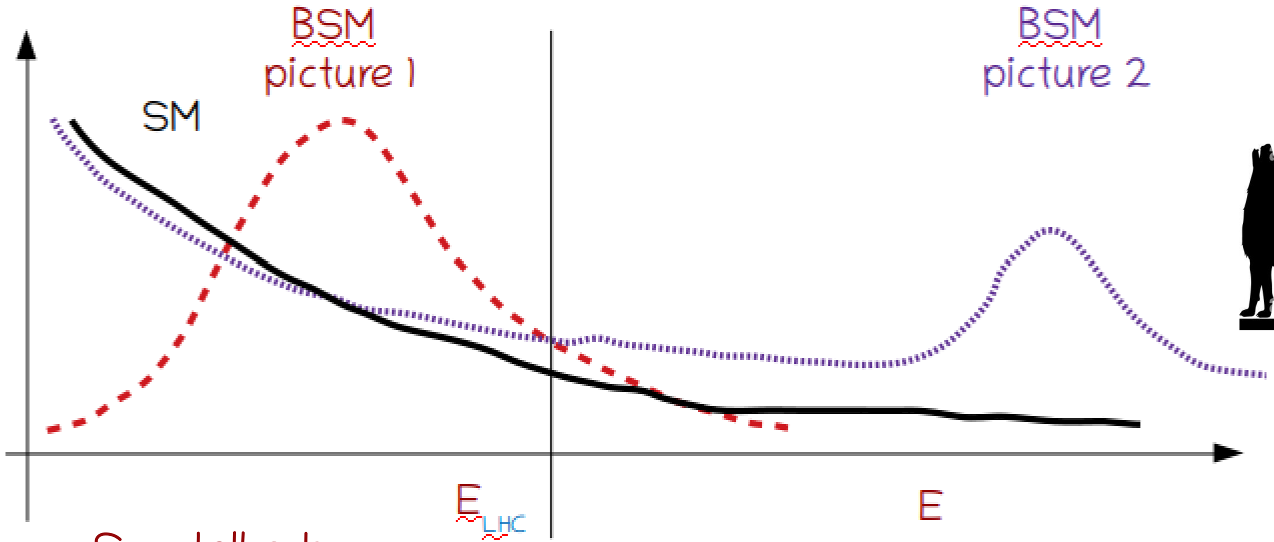
A. Malara
A. Agapitos

Discovery through
precision measurements

Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions





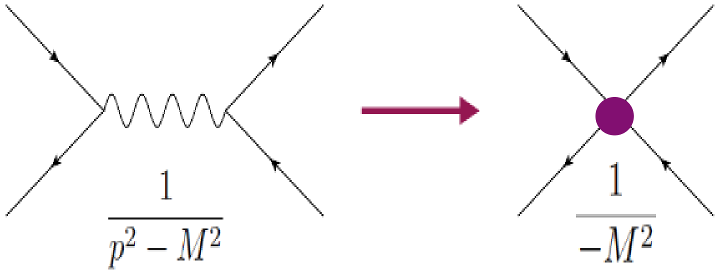
See talks by
A. Malara
A. Agapitos

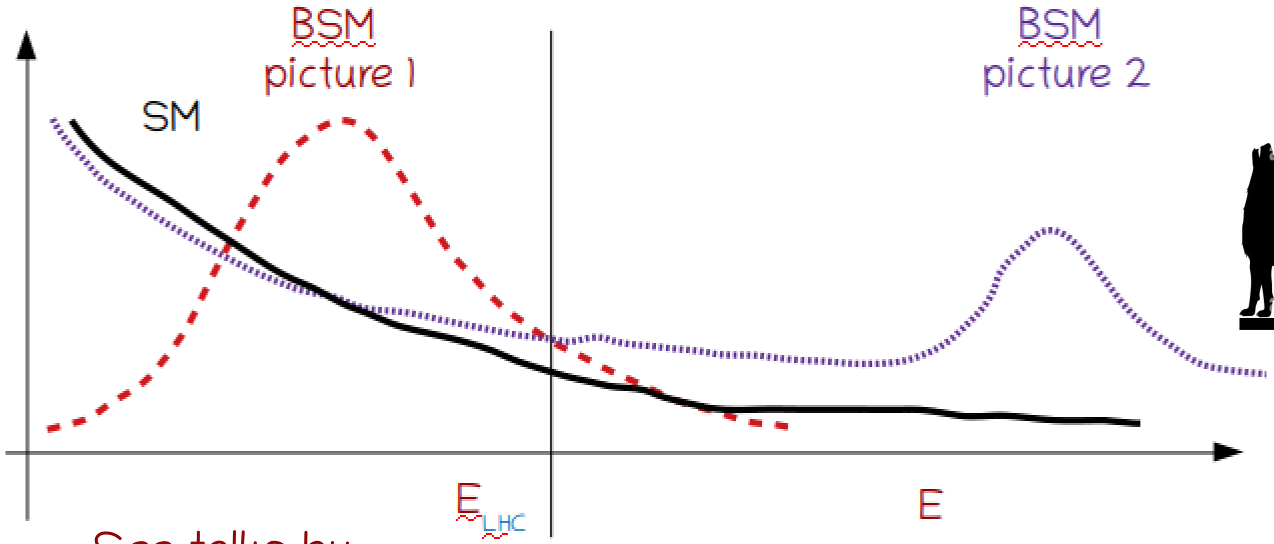
Discovery through precision measurements

Deviations from SM ← parameterized by effective field theory operators

Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions





See talks by

A. Malara
A. Agapitos

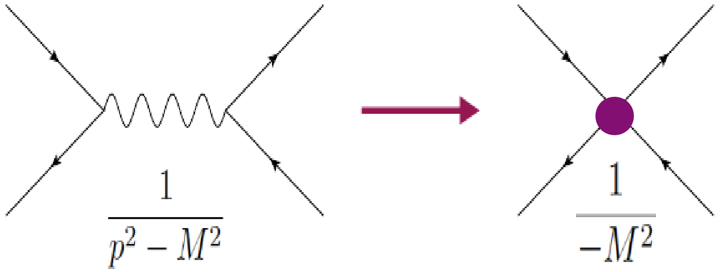
Discovery through
precision measurements

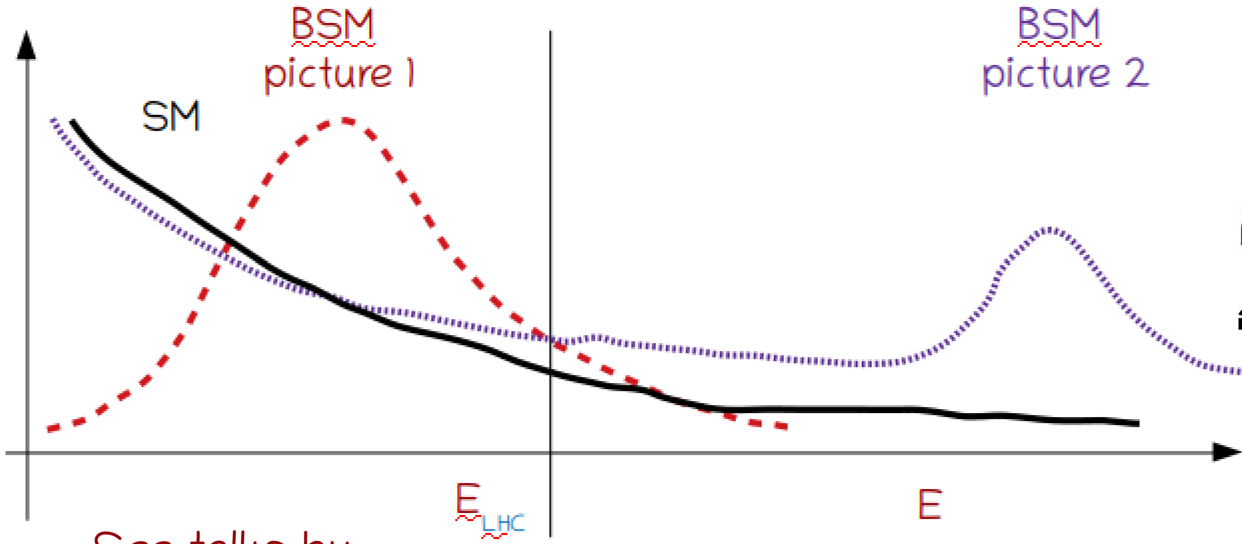
Deviations from SM ← parameterized by effective field theory operators

$$\mathcal{L}_{\text{SMEFT}} = \mathcal{L}_{\text{SM}} + \sum_i \frac{c_i^{(5)}}{\Lambda}\mathcal{O}_{5,i} + \sum_i \frac{c_i^{(6)}}{\Lambda^2}\mathcal{O}_{6,i} + \sum_i \frac{c_i^{(7)}}{\Lambda^3}\mathcal{O}_{7,i} + \sum_i \frac{c_i^{(8)}}{\Lambda^4}\mathcal{O}_{8,i} + \dots \,.$$

Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions





See talks by

A. Malara

A. Agapitos

Discovery through precision measurements

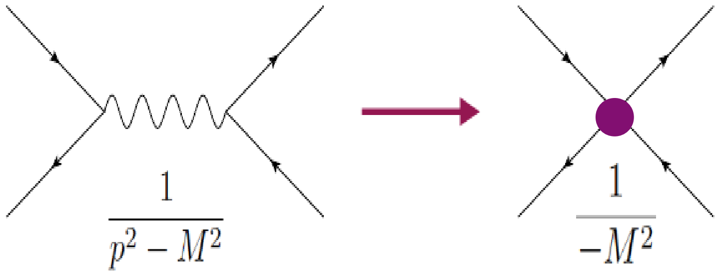
Deviations from SM ← parameterized by effective field theory operators

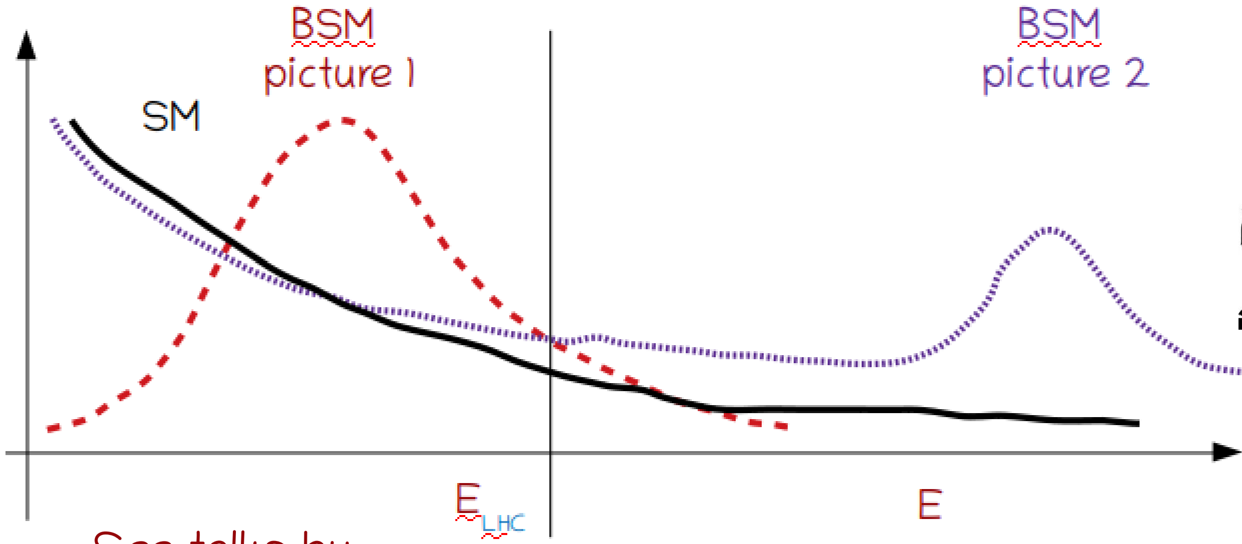
$$\mathcal{L}_{\rm SMEFT} = \mathcal{L}_{\rm SM} + \cancel{\sum_i \frac{c_i^{(5)}}{\Lambda} \mathcal{O}_{5,i}} + \sum_i \frac{c_i^{(6)}}{\Lambda^2} \mathcal{O}_{6,i} + \sum_i \frac{c_i^{(7)}}{\Lambda^3} \mathcal{O}_{7,i} + \sum_i \frac{c_i^{(8)}}{\Lambda^4} \mathcal{O}_{8,i} + \dots .$$

Lepton number violation

Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions





See talks by

A. Malara
A. Agapitos

Discovery through precision measurements

Deviations from SM ← parameterized by effective field theory operators

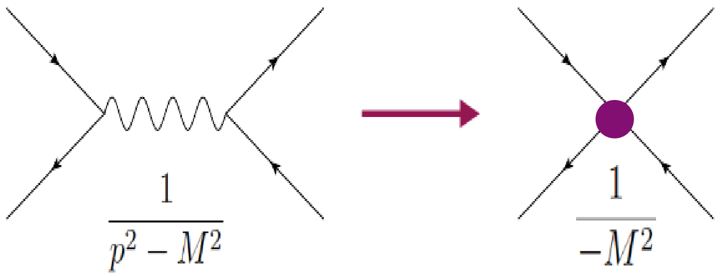
$$\mathcal{L}_{\rm SMEFT} = \mathcal{L}_{\rm SM} + \sum_i \cancel{\frac{c_i^{(5)}}{\Lambda}\mathcal{O}_{5,i}} + \sum_i \frac{c_i^{(6)}}{\Lambda^2}\mathcal{O}_{6,i} + \sum_i \cancel{\frac{c_i^{(7)}}{\Lambda^3}\mathcal{O}_{7,i}} + \sum_i \frac{c_i^{(8)}}{\Lambda^4}\mathcal{O}_{8,i} + \dots .$$

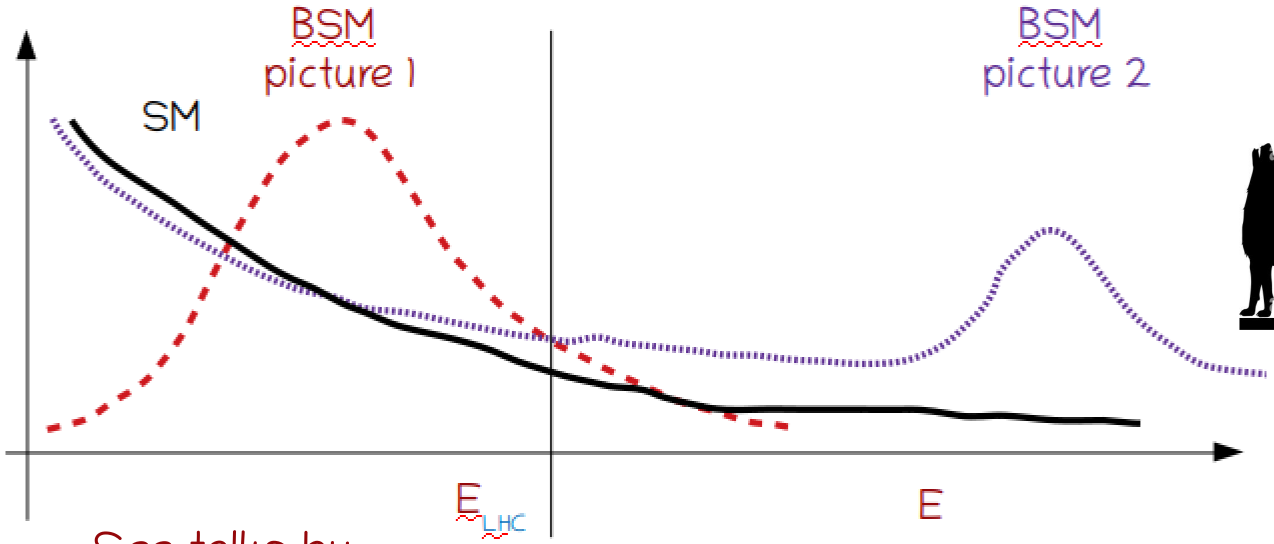
Lepton number violation

Lepton & Baryon number violation

Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions





See talks by

A. Malara
A. Agapitos

Discovery through precision measurements

Deviations from SM ← parameterized by effective field theory operators

$$\mathcal{L}_{\text{SMEFT}} = \mathcal{L}_{\text{SM}} + \cancel{\sum_i \frac{c_i^{(5)}}{\Lambda} \mathcal{O}_{5,i}} + \boxed{\sum_i \frac{c_i^{(6)}}{\Lambda^2} \mathcal{O}_{6,i}} + \cancel{\sum_i \frac{c_i^{(7)}}{\Lambda^3} \mathcal{O}_{7,i}} + \sum_i \frac{c_i^{(8)}}{\Lambda^4} \mathcal{O}_{8,i} + \ldots .$$

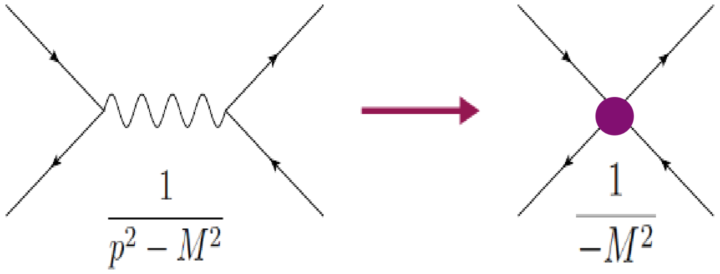
Lepton number violation

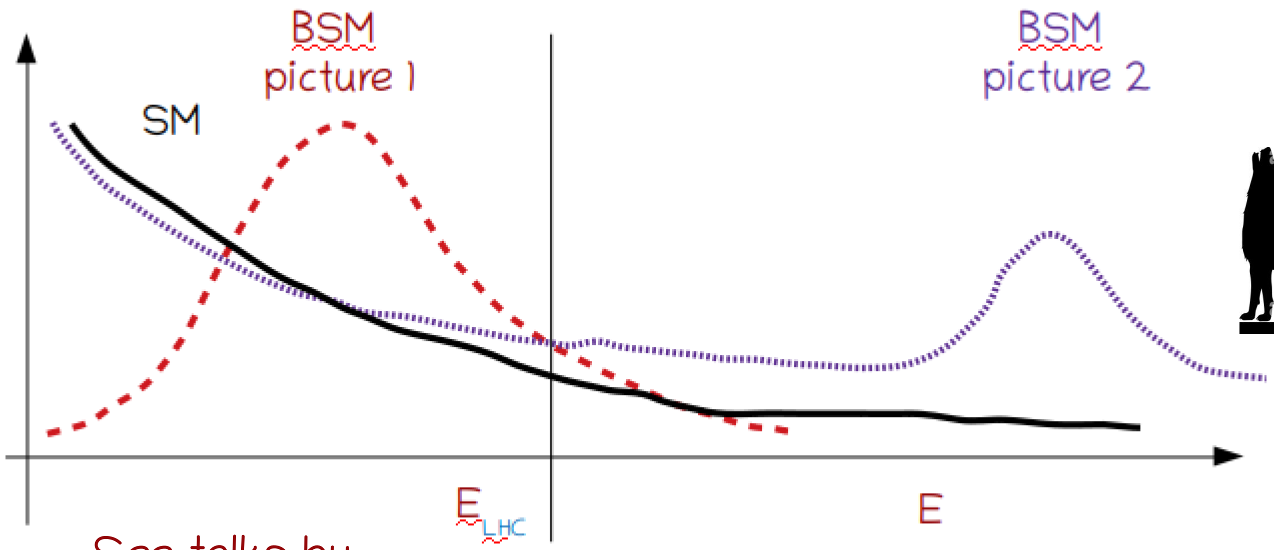
Lepton & Baryon number violation

59 SMEFT operators @ dim=6 Grzadkowski, Iskrzyński, Misiak, Rosiek (2010)

Standard model effective field theory (SMEFT)

New (heavy) particles modify SM interactions





See talks by

A. Malara

A. Agapitos

Discovery through precision measurements

Deviations from SM ← parameterized by effective field theory operators

$$\mathcal{L}_{\rm SMEFT} = \mathcal{L}_{\rm SM} + \cancel{\sum_i \frac{c_i^{(5)}}{\Lambda}\mathcal{O}_{5,i}} + \boxed{\sum_i \frac{c_i^{(6)}}{\Lambda^2}\mathcal{O}_{6,i}} + \cancel{\sum_i \frac{c_i^{(7)}}{\Lambda^3}\mathcal{O}_{7,i}} + \sum_i \frac{c_i^{(8)}}{\Lambda^4}\mathcal{O}_{8,i} + \dots\,.$$

Lepton number violation

Lepton & Baryon number violation

Assumptions:

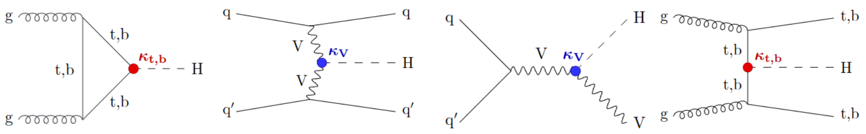
→ Particle content same as in SM

→ SM Gauge symmetries $SU(3)_C$ x $SU(2)_L$ x $U(1)_Y$ respected

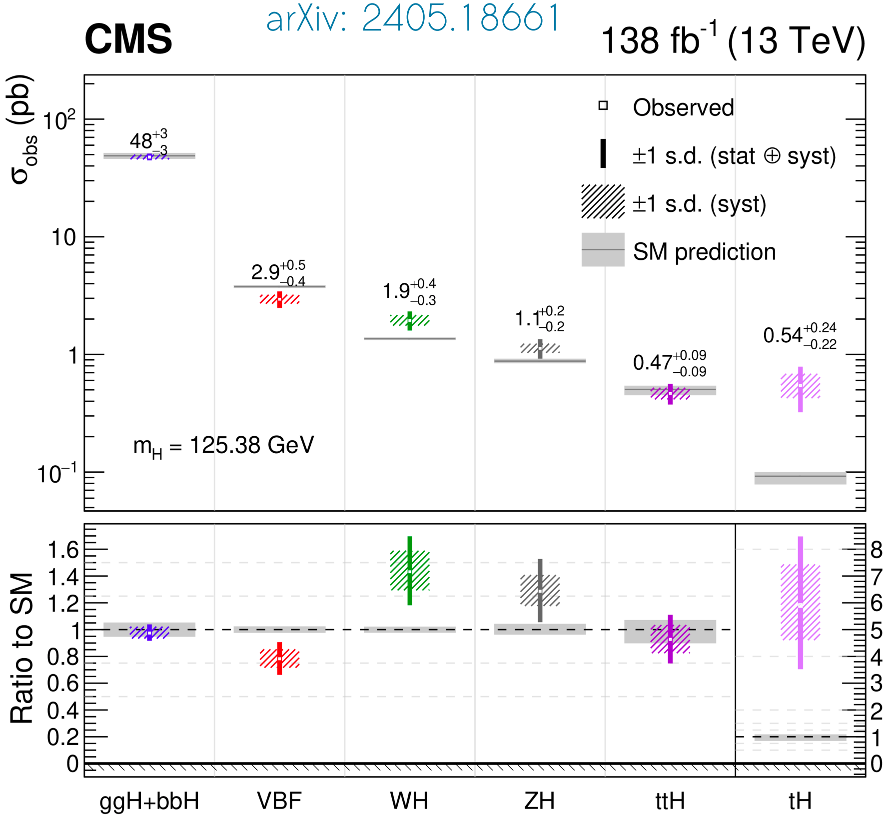
59 SMEFT operators @ dim=6 Grzadkowski, Iskrzyński, Misiak, Rosiek (2010)

Higgstrahlung: small but important

H production

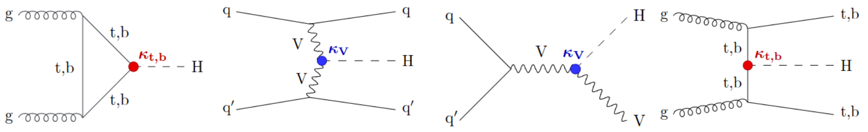


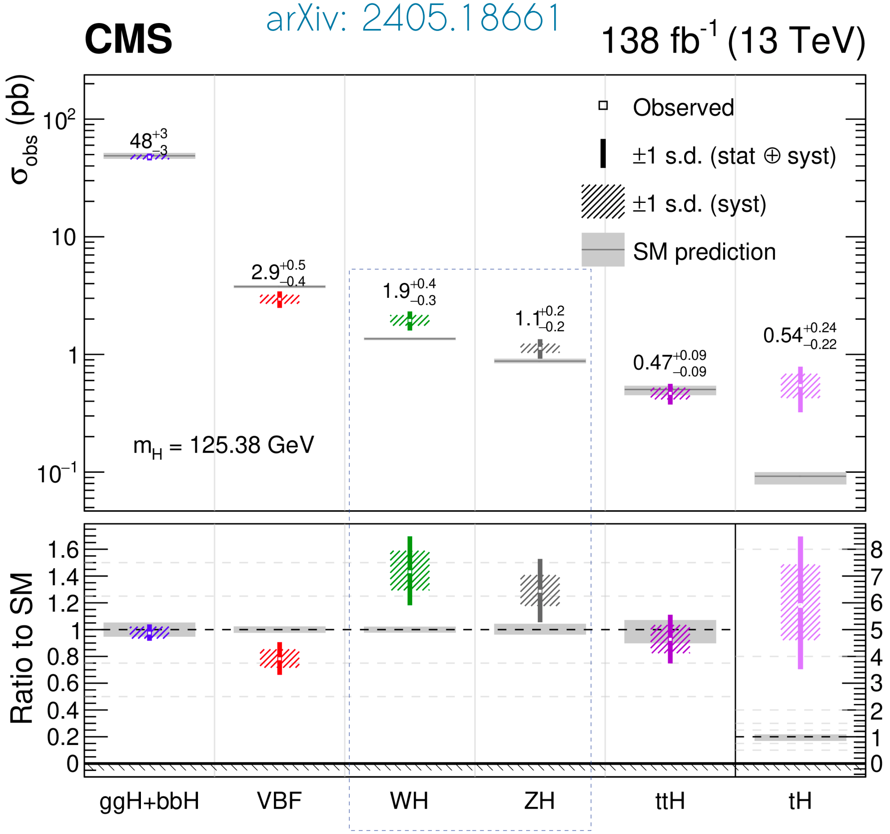
arXiv: 2405.18661



Higgstrahlung: small but important

H production



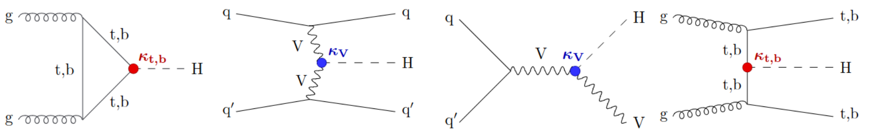


arXiv: 2405.18661

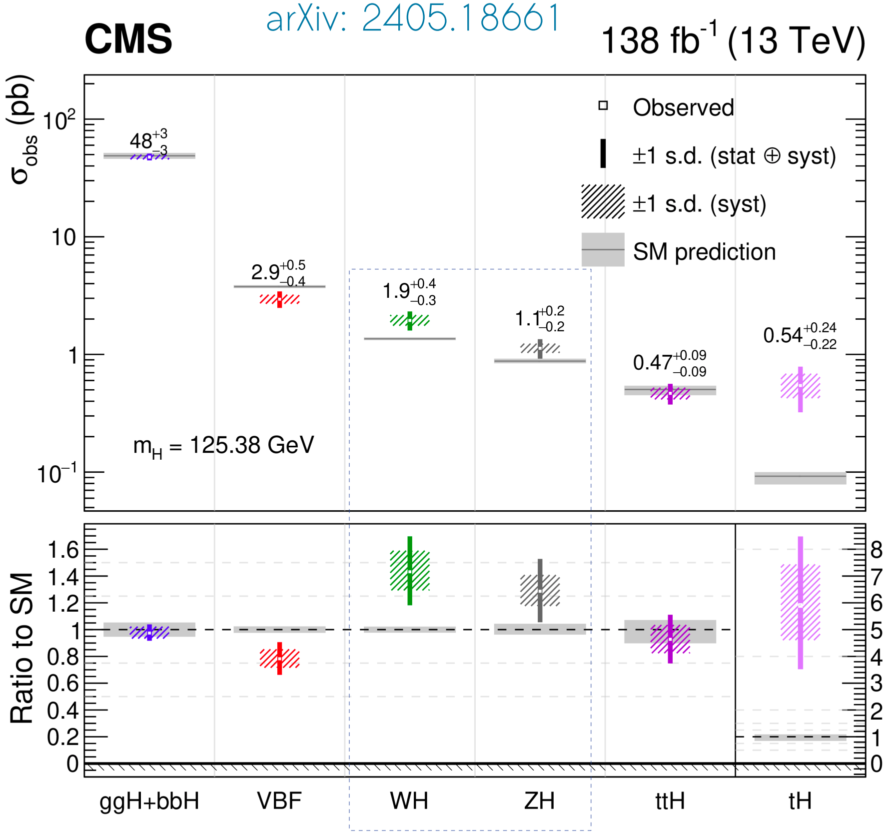
WH/ZH → small production cross section

Higgstrahlung: small but important

H production



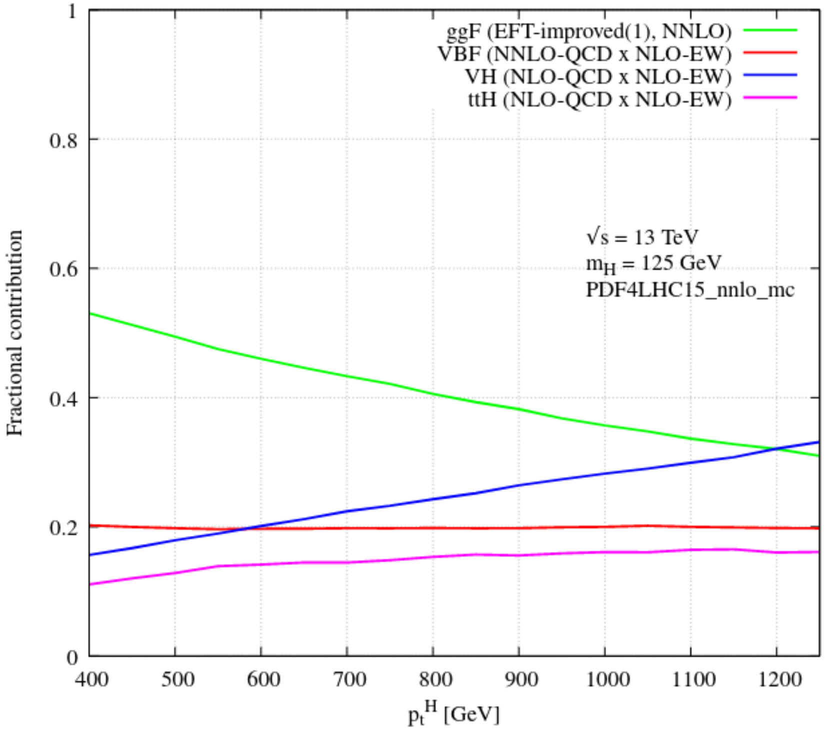
arXiv: 2405.18661



WH/ZH → small production cross section

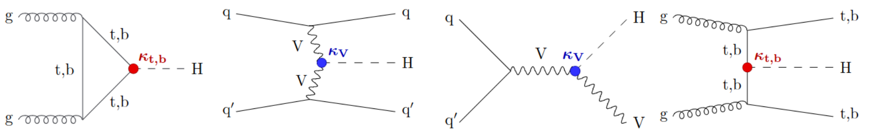
Higgs-strahlung important at high energy

LHCHXSWG-2019-002

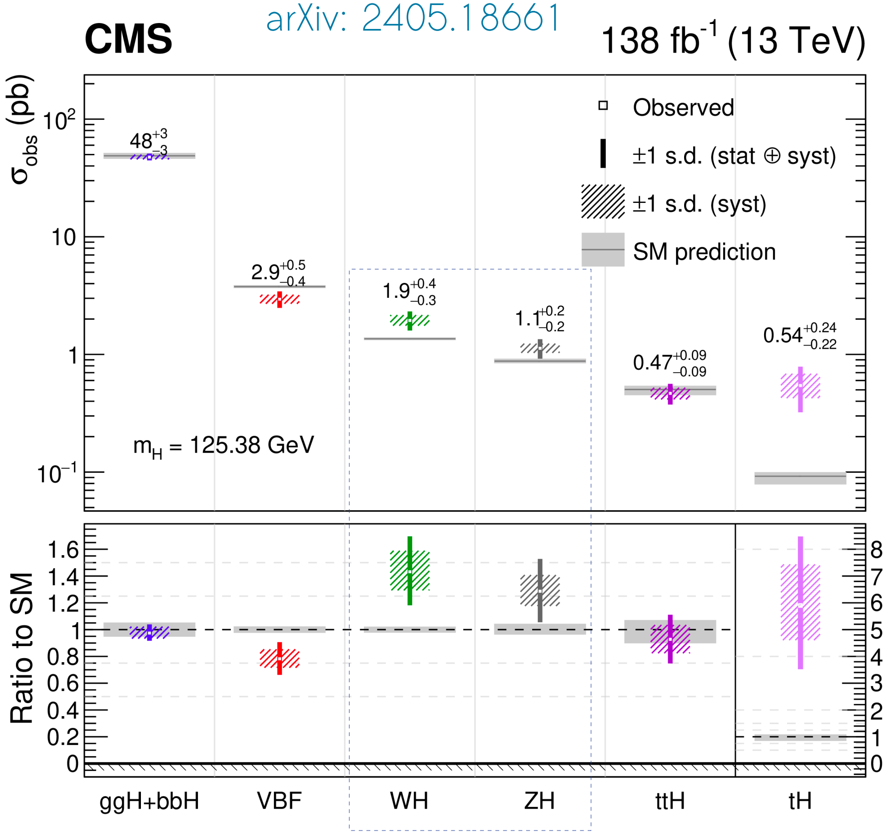


Higgsstrahlung: small but important

H production



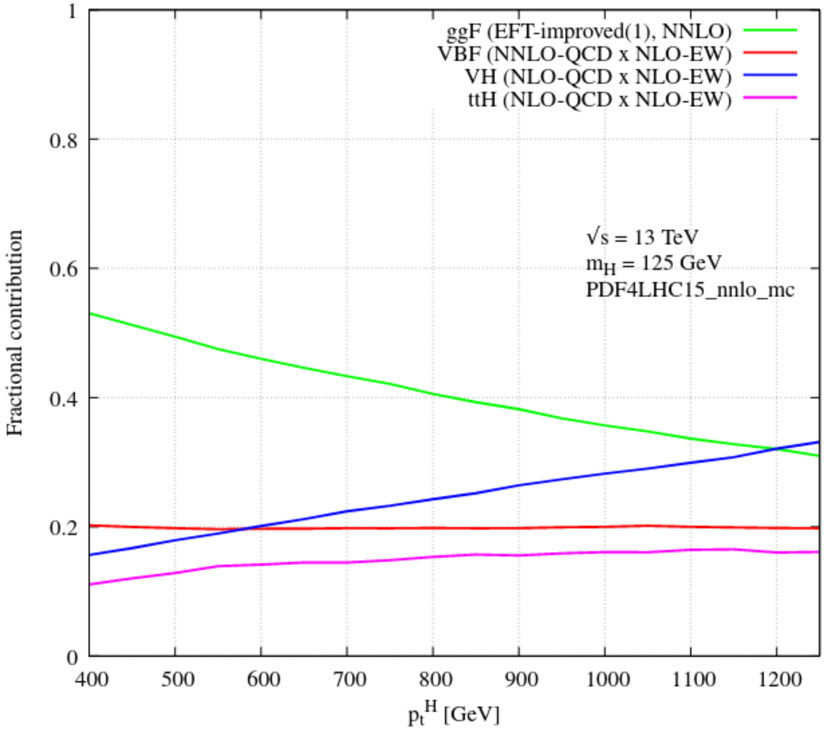
arXiv: 2405.18661



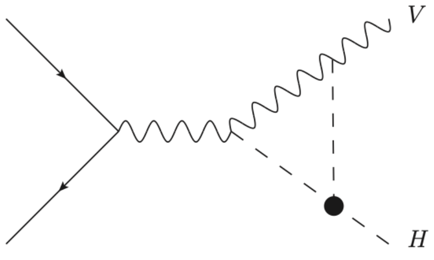
WH/ZH → small production cross section

Higgs-strahlung important at high energy

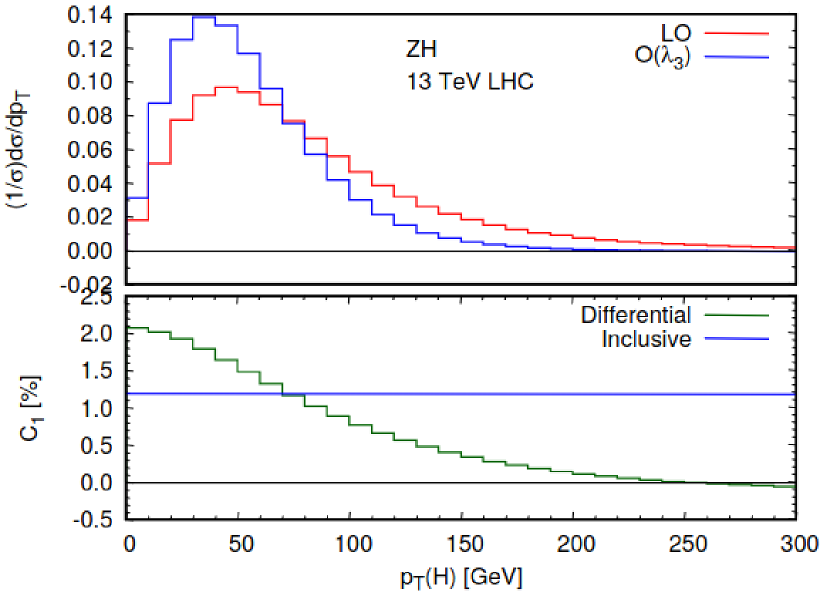
LHCHXSWG-2019-002



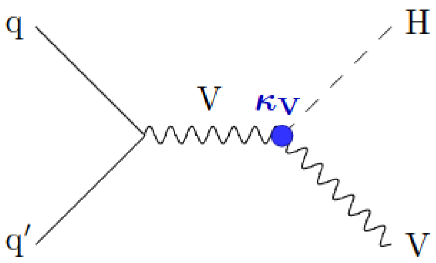
Sensitive to Higgs self-coupling



Maltoni, Pagani, Shivaji, Zhao (2017)



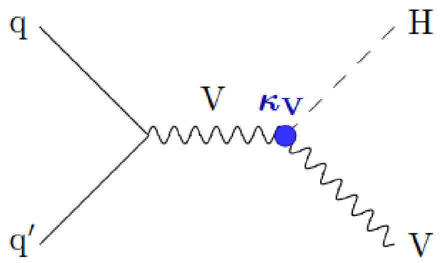
Cross section measurement of V associated H production @CMS



Small production cross section

- H→ bb decay ← largest branching ratio
- V→ leptons ← clean signature

Cross section measurement of V associated H production @CMS

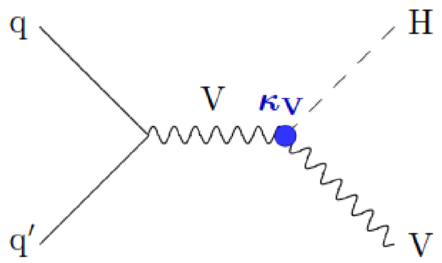


Phys.Rev.D 109 (2024) 9, 092011

Small production cross section

- H→ bb decay ← largest branching ratio
- V→ leptons ← clean signature

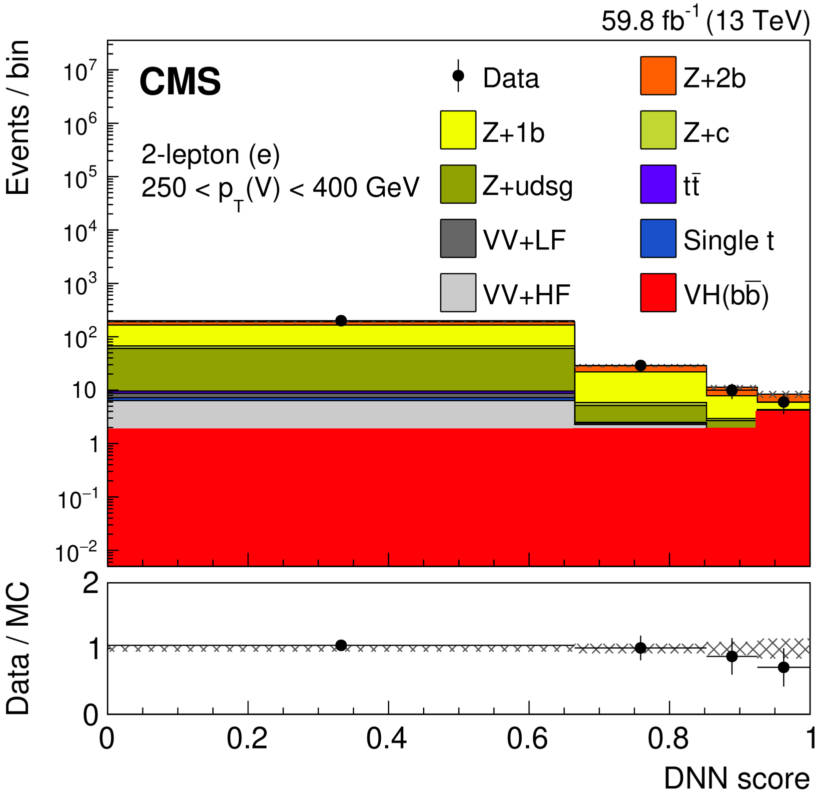
Cross section measurement of V associated H production @CMS



Phys.Rev.D 109 (2024) 9, 092011

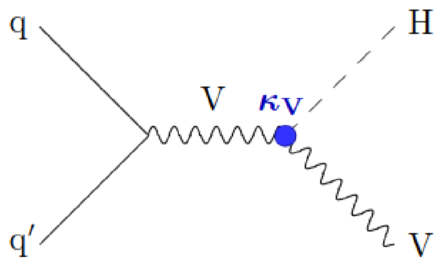
Small production cross section

- H→ bb decay ← largest branching ratio
- V→ leptons ← clean signature



VH signal extracted using DNN score in signal-enriched regions

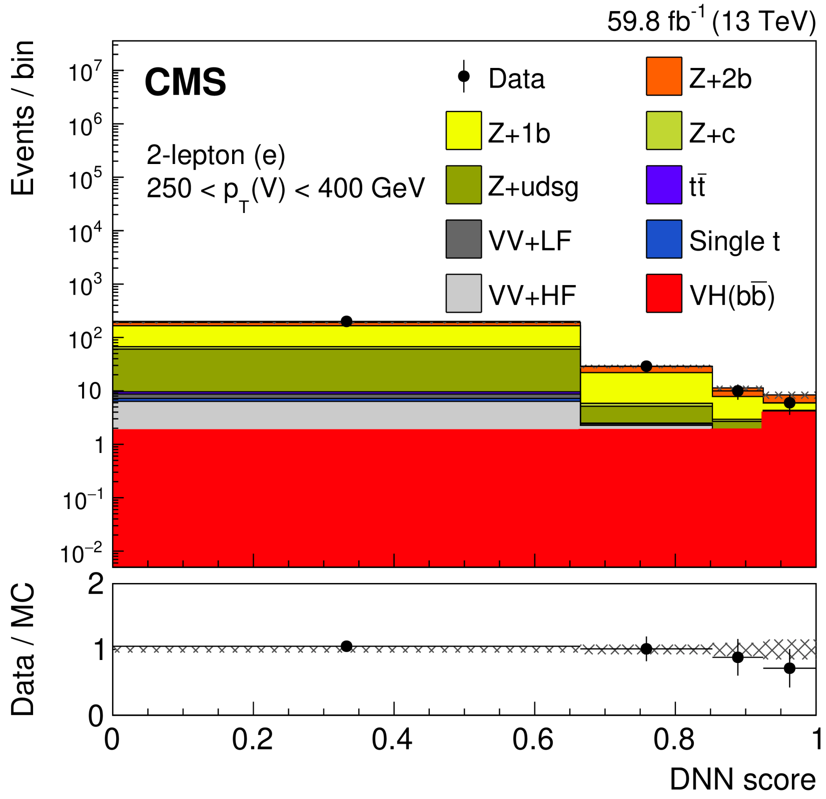
Cross section measurement of V associated H production @CMS

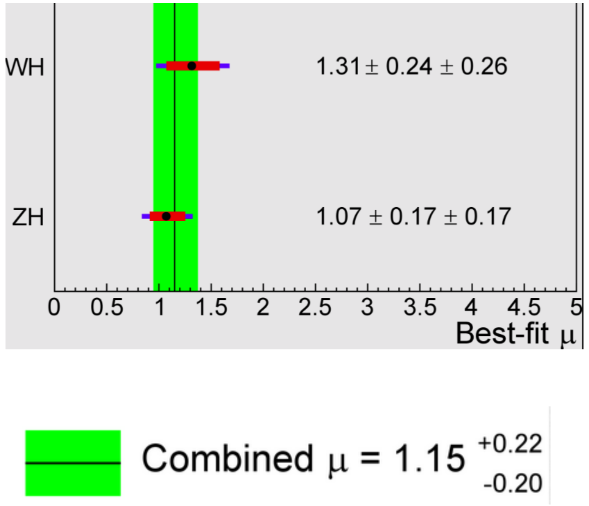


Phys.Rev.D 109 (2024) 9, 092011

Small production cross section

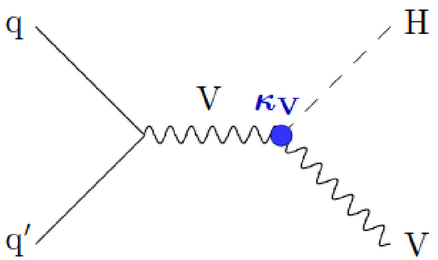
- H→ bb decay ← largest branching ratio
- V→ leptons ← clean signature





VH signal extracted using DNN score in signal-enriched regions

Cross section measurement of V associated H production @CMS

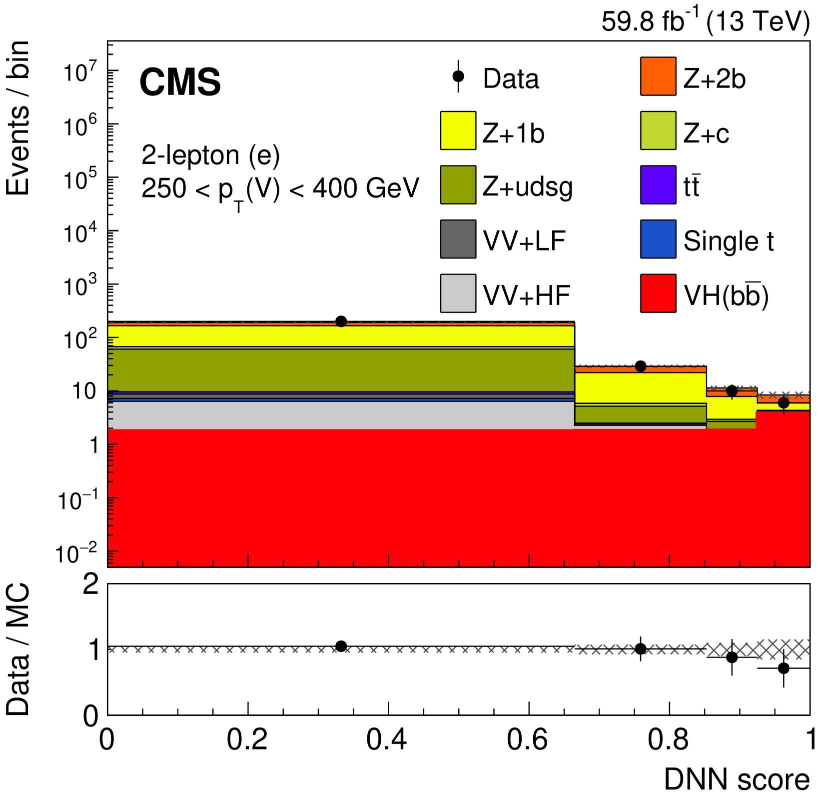


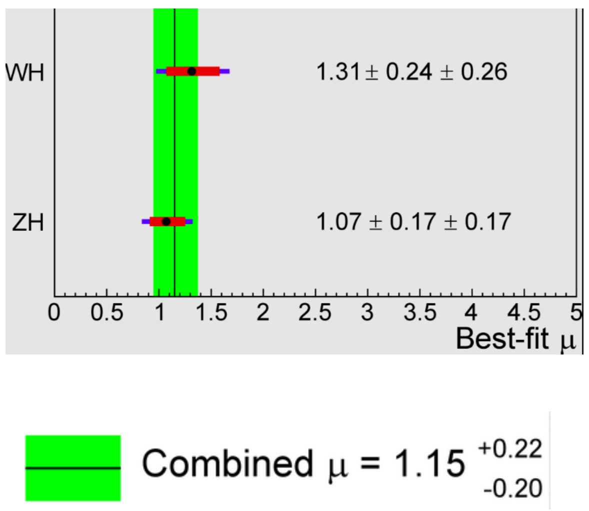
Phys.Rev.D 109 (2024) 9, 092011

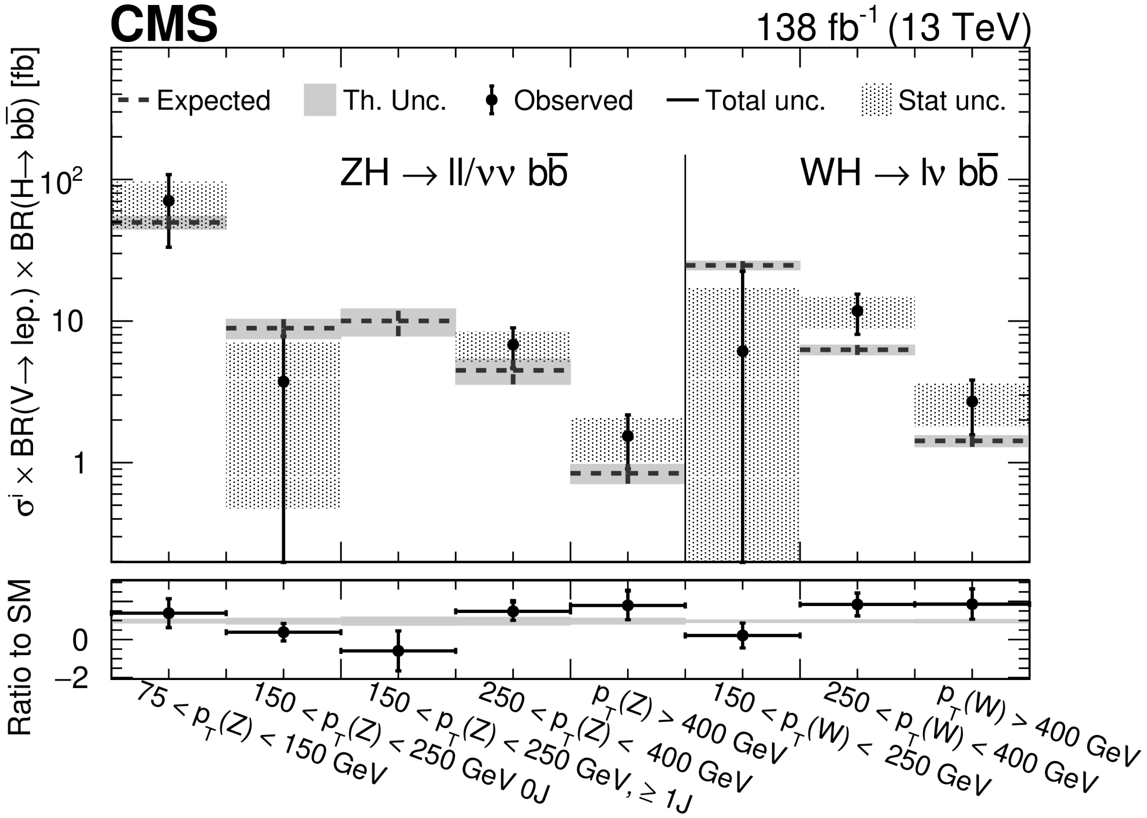
Small production cross section

- H→ bb decay ← largest branching ratio
- V→ leptons ← clean signature

Cross section reported in simplified template cross section framework

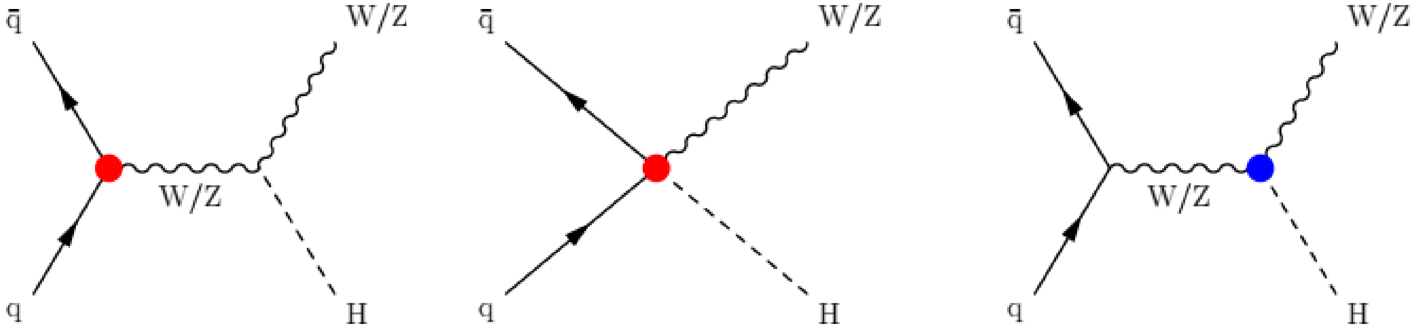






VH signal extracted using DNN score in signal-enriched regions

EFT effects in V associated H production



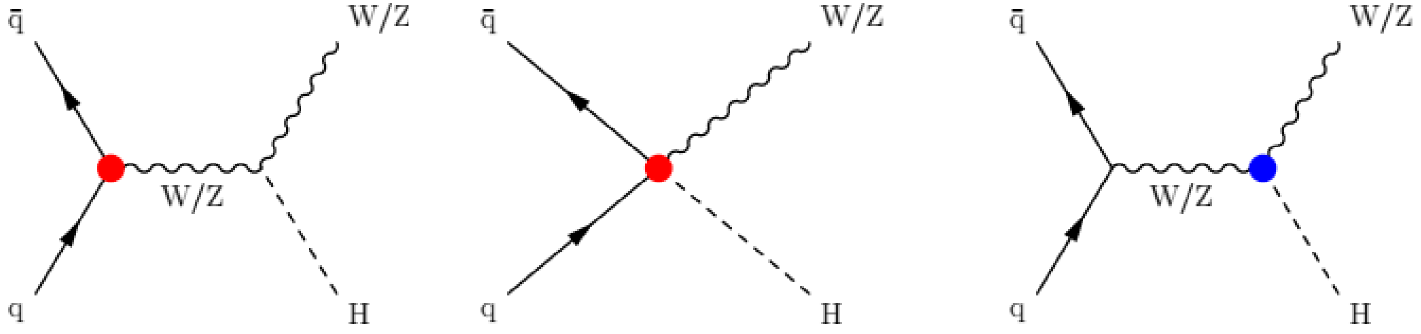
Current operators

$\mathcal{O}^{(1)}_{\mathrm{Hq}}$	$i\mathrm{H}^\dagger \overleftrightarrow{D}_\mu \mathrm{H} \bar{\mathrm{q}}_\mathrm{L} \gamma^\mu \mathrm{q}_\mathrm{L}$	$c^{(1)}_{\mathrm{Hq}}$
$\mathcal{O}^{(3)}_{\mathrm{Hq}}$	$i\mathrm{H}^\dagger \sigma^a \overleftrightarrow{D}_\mu \mathrm{H} \bar{\mathrm{q}}_\mathrm{L} \sigma^a \gamma^\mu \mathrm{q}_\mathrm{L}$	$c^{(3)}_{\mathrm{Hq}}$
$\mathcal{O}_{\mathrm{Hu}}$	$i\mathrm{H}^\dagger \overleftrightarrow{D}_\mu \mathrm{H} \bar{\mathrm{u}}_\mathrm{R} \gamma^\mu \mathrm{u}_\mathrm{R}$	c_{Hu}
$\mathcal{O}_{\mathrm{Hd}}$	$i\mathrm{H}^\dagger \overleftrightarrow{D}_\mu \mathrm{H} \bar{\mathrm{d}}_\mathrm{R} \gamma^\mu \mathrm{d}_\mathrm{R}$	c_{Hd}

Gauge coupling operators

$\mathcal{O}_{\mathrm{HWB}}$	$\mathrm{H}^\dagger \sigma^a \mathrm{H} \mathrm{W}^a_{\mu\nu} \mathrm{B}^{\mu\nu}$	c_{HWB}
$\mathcal{O}_{\mathrm{HW}}$	$(\mathrm{H}^\dagger \mathrm{H})\, \mathrm{W}^a_{\mu\nu} \mathrm{W}^{a\mu\nu}$	c_{HW}
$\mathcal{O}_{\mathrm{HB}}$	$(\mathrm{H}^\dagger \mathrm{H})\, \mathrm{B}_{\mu\nu} \mathrm{B}^{\mu\nu}$	c_{HB}
$\mathcal{O}_{\mathrm{H\widetilde{W}B}}$	$\mathrm{H}^\dagger \sigma^a \mathrm{H} \mathrm{W}^a_{\mu\nu} \widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{W}B}}$
$\mathcal{O}_{\mathrm{H\widetilde{W}}}$	$(\mathrm{H}^\dagger \mathrm{H})\, \mathrm{W}^a_{\mu\nu} \widetilde{\mathrm{W}}^{a\mu\nu}$	$c_{\mathrm{H\widetilde{W}}}$
$\mathcal{O}_{\mathrm{H\tilde{B}}}$	$(\mathrm{H}^\dagger \mathrm{H})\, \mathrm{B}_{\mu\nu} \widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\tilde{B}}}$

EFT effects in V associated H production



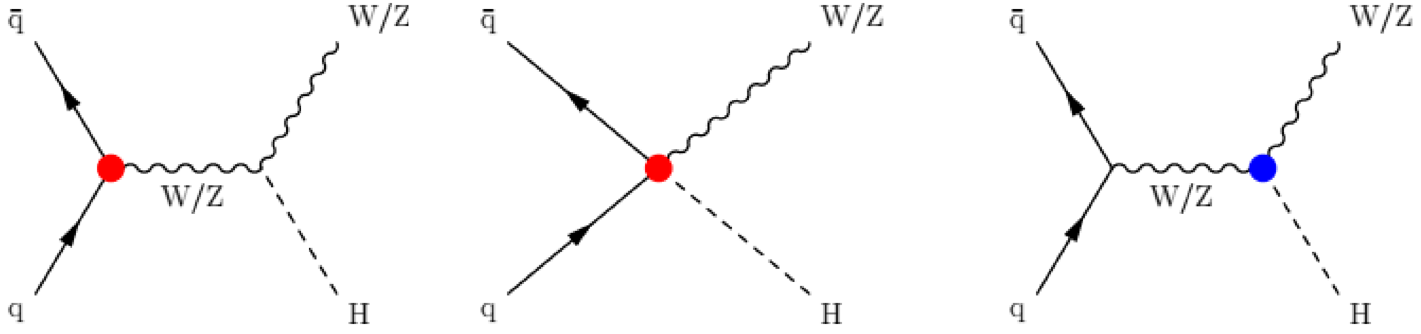
Current operators

$\mathcal{O}_{Hq}^{(1)}$	$iH^\dagger \overleftrightarrow{D}_\mu H \bar{q}_L \gamma^\mu q_L$	$c_{Hq}^{(1)}$
$\mathcal{O}_{Hq}^{(3)}$	$iH^\dagger \sigma^a \overleftrightarrow{D}_\mu H \bar{q}_L \sigma^a \gamma^\mu q_L$	$c_{Hq}^{(3)}$
$\mathcal{O}_{Hu}$	$iH^\dagger \overleftrightarrow{D}_\mu H \bar{u}_R \gamma^\mu u_R$	c_{Hu}
$\mathcal{O}_{Hd}$	$iH^\dagger \overleftrightarrow{D}_\mu H \bar{d}_R \gamma^\mu d_R$	c_{Hd}

Gauge coupling operators

$\mathcal{O}_{HWB}$	$H^\dagger \sigma^a H W^a_{\mu\nu} B^{\mu\nu}$	c_{HWB}
$\mathcal{O}_{HW}$	$(H^\dagger H)\, W^a_{\mu\nu} W^{a\mu\nu}$	c_{HW}
$\mathcal{O}_{HB}$	$(H^\dagger H)\, B_{\mu\nu} B^{\mu\nu}$	c_{HB}
$\mathcal{O}_{H\widetilde{W}B}$	$H^\dagger \sigma^a H W^a_{\mu\nu} \widetilde{B}^{\mu\nu}$	$c_{H\widetilde{W}B}$
$\mathcal{O}_{H\widetilde{W}}$	$(H^\dagger H)\, W^a_{\mu\nu} \widetilde{W}^{a\mu\nu}$	$c_{H\widetilde{W}}$
$\mathcal{O}_{H\tilde{B}}$	$(H^\dagger H)\, B_{\mu\nu} \widetilde{B}^{\mu\nu}$	$c_{H\tilde{B}}$

EFT effects in V associated H production



Rotation to mass eigenstate basis

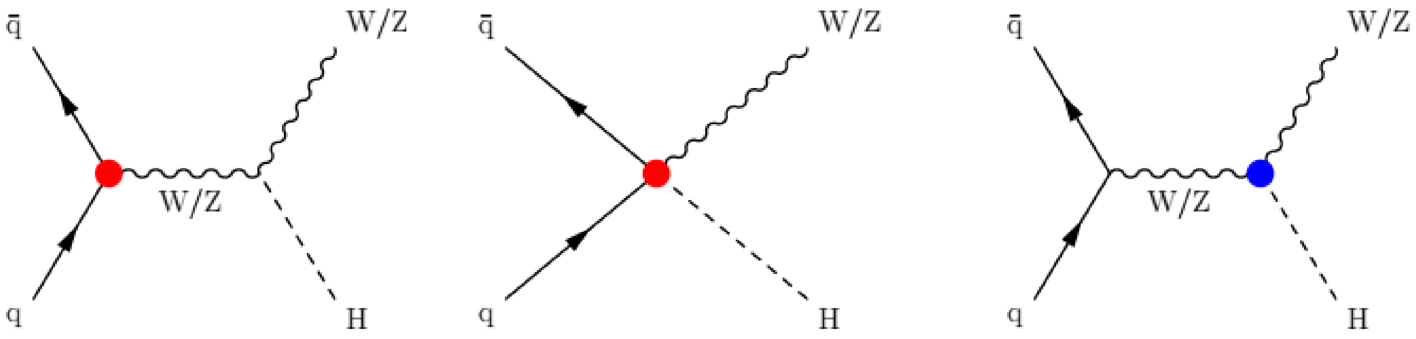
Current operators

$\mathcal{O}^{(1)}_{\mathrm{Hq}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c^{(1)}_{\mathrm{Hq}}$
$\mathcal{O}^{(3)}_{\mathrm{Hq}}$	$i\mathrm{H}^{\dagger}\sigma^{a}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\sigma^{a}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c^{(3)}_{\mathrm{Hq}}$
$\mathcal{O}_{\mathrm{Hu}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{u}}_{\mathrm{R}}\gamma^{\mu}\mathrm{u}_{\mathrm{R}}$	c_{Hu}
$\mathcal{O}_{\mathrm{Hd}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{d}}_{\mathrm{R}}\gamma^{\mu}\mathrm{d}_{\mathrm{R}}$	c_{Hd}

Gauge coupling operators

$\mathcal{O}_{\mathrm{HWB}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}\mathrm{W}^{a}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HWB}
$\mathcal{O}_{\mathrm{HW}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\mathrm{W}^{a\mu\nu}$	c_{HW}
$\mathcal{O}_{\mathrm{HB}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HB}
$\mathcal{O}_{\mathrm{H\widetilde{W}B}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{W}B}}$
$\mathcal{O}_{\mathrm{H\widetilde{W}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{W}}^{a\mu\nu}$	$c_{\mathrm{H\widetilde{W}}}$
$\mathcal{O}_{\mathrm{H\tilde{B}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\tilde{B}}}$

EFT effects in V associated H production



Current operators

$\mathcal{O}_{\mathrm{Hq}}^{(1)}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c_{\mathrm{Hq}}^{(1)}$
$\mathcal{O}_{\mathrm{Hq}}^{(3)}$	$i\mathrm{H}^{\dagger}\sigma^{a}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\sigma^{a}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c_{\mathrm{Hq}}^{(3)}$
$\mathcal{O}_{\mathrm{Hu}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{u}}_{\mathrm{R}}\gamma^{\mu}\mathrm{u}_{\mathrm{R}}$	c_{Hu}
$\mathcal{O}_{\mathrm{Hd}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{d}}_{\mathrm{R}}\gamma^{\mu}\mathrm{d}_{\mathrm{R}}$	c_{Hd}

Gauge coupling operators

$\mathcal{O}_{\mathrm{HWB}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}\mathrm{W}^{a}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HWB}
$\mathcal{O}_{\mathrm{HW}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\mathrm{W}^{a\mu\nu}$	c_{HW}
$\mathcal{O}_{\mathrm{HB}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HB}
$\mathcal{O}_{\mathrm{H\widetilde{W}B}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{W}B}}$
$\mathcal{O}_{\mathrm{H\widetilde{W}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{W}}^{a\mu\nu}$	$c_{\mathrm{H\widetilde{W}}}$
$\mathcal{O}_{\mathrm{H\widetilde{B}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{B}}}$

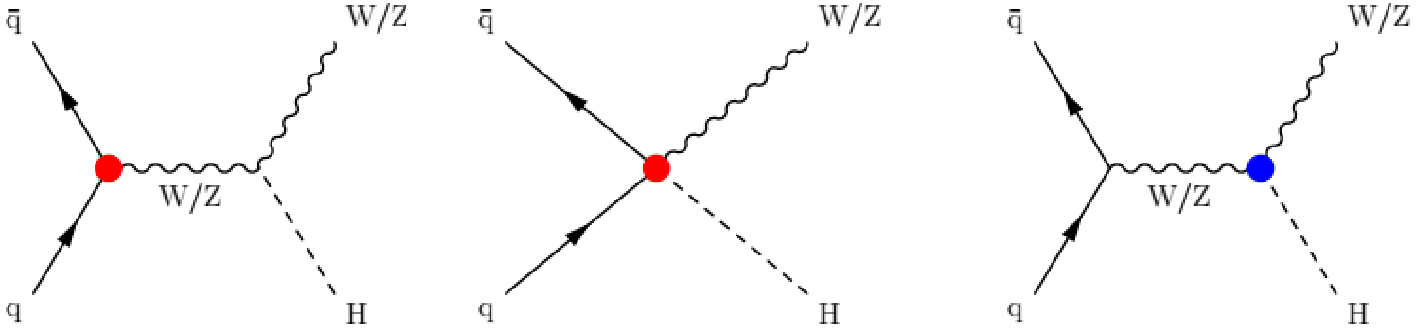
Rotation to mass eigenstate basis

$$g_2^{ZZ} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{HB}} + c_w^2 c_{\mathrm{HW}} + s_w c_w c_{\mathrm{HWB}}\right),$$

$$g_2^{Z\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{HW}} - c_{\mathrm{HB}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{HWB}}\right),$$

$$g_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{HB}} + s_w^2 c_{\mathrm{HW}} - s_w c_w c_{\mathrm{HWB}}\right),$$

EFT effects in V associated H production



Current operators

$\mathcal{O}_{\mathrm{Hq}}^{(1)}$	$i\mathrm{H}^\dagger \overleftrightarrow{D}_\mu \mathrm{H} \bar{\mathrm{q}}_\mathrm{L} \gamma^\mu \mathrm{q}_\mathrm{L}$	$c_{\mathrm{Hq}}^{(1)}$
$\mathcal{O}_{\mathrm{Hq}}^{(3)}$	$i\mathrm{H}^\dagger \sigma^a \overleftrightarrow{D}_\mu \mathrm{H} \bar{\mathrm{q}}_\mathrm{L} \sigma^a \gamma^\mu \mathrm{q}_\mathrm{L}$	$c_{\mathrm{Hq}}^{(3)}$
$\mathcal{O}_{\mathrm{Hu}}$	$i\mathrm{H}^\dagger \overleftrightarrow{D}_\mu \mathrm{H} \bar{\mathrm{u}}_\mathrm{R} \gamma^\mu \mathrm{u}_\mathrm{R}$	c_{Hu}
$\mathcal{O}_{\mathrm{Hd}}$	$i\mathrm{H}^\dagger \overleftrightarrow{D}_\mu \mathrm{H} \bar{\mathrm{d}}_\mathrm{R} \gamma^\mu \mathrm{d}_\mathrm{R}$	c_{Hd}

Gauge coupling operators

$\mathcal{O}_{\mathrm{HWB}}$	$\mathrm{H}^\dagger \sigma^a \mathrm{H} \mathrm{W}^a_{\mu\nu} \mathrm{B}^{\mu\nu}$	c_{HWB}
$\mathcal{O}_{\mathrm{HW}}$	$(\mathrm{H}^\dagger \mathrm{H})\, \mathrm{W}^a_{\mu\nu} \mathrm{W}^{a\mu\nu}$	c_{HW}
$\mathcal{O}_{\mathrm{HB}}$	$(\mathrm{H}^\dagger \mathrm{H})\, \mathrm{B}_{\mu\nu} \mathrm{B}^{\mu\nu}$	c_{HB}
$\mathcal{O}_{\mathrm{H\widetilde{W}B}}$	$\mathrm{H}^\dagger \sigma^a \mathrm{H} \mathrm{W}^a_{\mu\nu} \widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{W}B}}$
$\mathcal{O}_{\mathrm{H\widetilde{W}}}$	$(\mathrm{H}^\dagger \mathrm{H})\, \mathrm{W}^a_{\mu\nu} \widetilde{\mathrm{W}}^{a\mu\nu}$	$c_{\mathrm{H\widetilde{W}}}$
$\mathcal{O}_{\mathrm{H\tilde{B}}}$	$(\mathrm{H}^\dagger \mathrm{H})\, \mathrm{B}_{\mu\nu} \widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\tilde{B}}}$

Rotation to mass eigenstate basis

$$g_2^{\mathrm{ZZ}} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{HB}} + c_w^2 c_{\mathrm{HW}} + s_w c_w c_{\mathrm{HWB}}\right),$$

$$g_2^{\mathrm{Z}\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{HW}} - c_{\mathrm{HB}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{HWB}}\right),$$

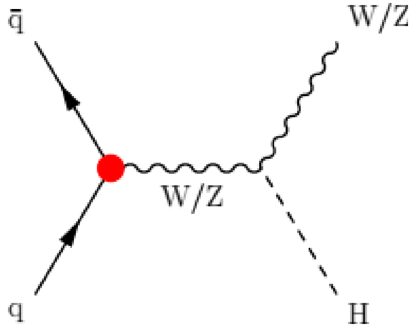
$$g_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{HB}} + s_w^2 c_{\mathrm{HW}} - s_w c_w c_{\mathrm{HWB}}\right),$$

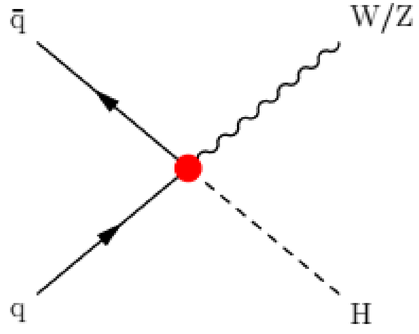
$$g_4^{\mathrm{ZZ}} = \tilde{g}_2^{\mathrm{ZZ}} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{H\tilde{B}}} + c_w^2 c_{\mathrm{H\widetilde{W}}} + s_w c_w c_{\mathrm{H\widetilde{W}B}}\right),$$

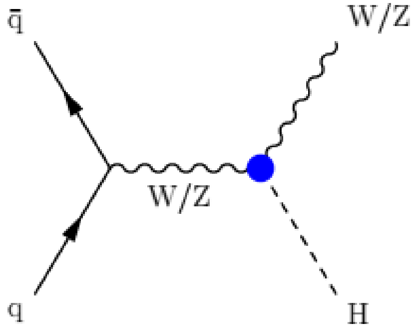
$$g_4^{\mathrm{Z}\gamma} = \tilde{g}_2^{\mathrm{Z}\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{H\widetilde{W}}} - c_{\mathrm{H\tilde{B}}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{H\widetilde{W}B}}\right),$$

$$g_4^{\gamma\gamma} = \tilde{g}_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{H\tilde{B}}} + s_w^2 c_{\mathrm{H\widetilde{W}}} - s_w c_w c_{\mathrm{H\widetilde{W}B}}\right).$$

EFT effects in V associated H production







Current operators

$\mathcal{O}_{\mathrm{Hq}}^{(1)}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c_{\mathrm{Hq}}^{(1)}$
$\mathcal{O}_{\mathrm{Hq}}^{(3)}$	$i\mathrm{H}^{\dagger}\sigma^{a}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\sigma^{a}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c_{\mathrm{Hq}}^{(3)}$
$\mathcal{O}_{\mathrm{Hu}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{u}}_{\mathrm{R}}\gamma^{\mu}\mathrm{u}_{\mathrm{R}}$	c_{Hu}
$\mathcal{O}_{\mathrm{Hd}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{d}}_{\mathrm{R}}\gamma^{\mu}\mathrm{d}_{\mathrm{R}}$	c_{Hd}

Gauge coupling operators

$\mathcal{O}_{\mathrm{HWB}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}W^{a}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HWB}
$\mathcal{O}_{\mathrm{HW}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\mathrm{W}^{a\mu\nu}$	c_{HW}
$\mathcal{O}_{\mathrm{HB}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HB}
$\mathcal{O}_{\mathrm{H\widetilde{W}B}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}W^{a}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{W}B}}$
$\mathcal{O}_{\mathrm{H\widetilde{W}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{W}}^{a\mu\nu}$	$c_{\mathrm{H\widetilde{W}}}$
$\mathcal{O}_{\mathrm{H\widetilde{B}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{B}}}$

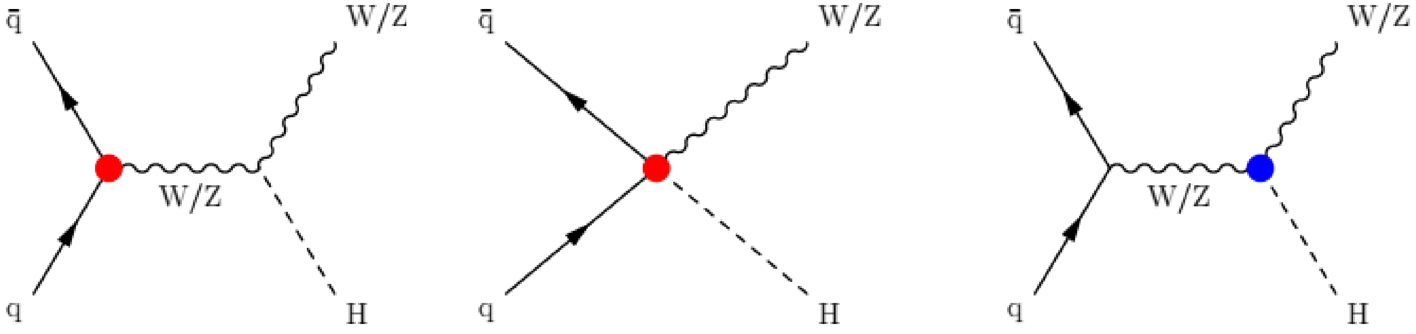
Rotation to mass eigenstate basis

$$g_2^{\mathrm{ZZ}} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{HB}} + c_w^2 c_{\mathrm{HW}} + s_w c_w c_{\mathrm{HWB}}\right),$$
$$g_2^{\mathrm{Z}\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{HW}} - c_{\mathrm{HB}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{HWB}}\right),$$
$$g_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{HB}} + s_w^2 c_{\mathrm{HW}} - s_w c_w c_{\mathrm{HWB}}\right),$$

$$c_w = \cos\theta_{\mathrm{W}}$$

$$g_4^{\mathrm{ZZ}} = \tilde{g}_2^{\mathrm{ZZ}} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{H\widetilde{B}}} + c_w^2 c_{\mathrm{H\widetilde{W}}} + s_w c_w c_{\mathrm{H\widetilde{W}B}}\right),$$
$$g_4^{\mathrm{Z}\gamma} = \tilde{g}_2^{\mathrm{Z}\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{H\widetilde{W}}} - c_{\mathrm{H\widetilde{B}}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{H\widetilde{W}B}}\right),$$
$$g_4^{\gamma\gamma} = \tilde{g}_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{H\widetilde{B}}} + s_w^2 c_{\mathrm{H\widetilde{W}}} - s_w c_w c_{\mathrm{H\widetilde{W}B}}\right).$$

EFT effects in V associated H production



Current operators

$\mathcal{O}_{\mathrm{Hq}}^{(1)}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c_{\mathrm{Hq}}^{(1)}$
$\mathcal{O}_{\mathrm{Hq}}^{(3)}$	$i\mathrm{H}^{\dagger}\sigma^{a}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\sigma^{a}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c_{\mathrm{Hq}}^{(3)}$
$\mathcal{O}_{\mathrm{Hu}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{u}}_{\mathrm{R}}\gamma^{\mu}\mathrm{u}_{\mathrm{R}}$	c_{Hu}
$\mathcal{O}_{\mathrm{Hd}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{d}}_{\mathrm{R}}\gamma^{\mu}\mathrm{d}_{\mathrm{R}}$	c_{Hd}

Gauge coupling operators

$\mathcal{O}_{\mathrm{HWB}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}\mathrm{W}^{a}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HWB}
$\mathcal{O}_{\mathrm{HW}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\mathrm{W}^{a\mu\nu}$	c_{HW}
$\mathcal{O}_{\mathrm{HB}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HB}
$\mathcal{O}_{\mathrm{H\widetilde{W}B}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{W}B}}$
$\mathcal{O}_{\mathrm{H\widetilde{W}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{W}}^{a\mu\nu}$	$c_{\mathrm{H\widetilde{W}}}$
$\mathcal{O}_{\mathrm{H\widetilde{B}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{B}}}$

Rotation to mass eigenstate basis

$$\boxed{g_2^{ZZ} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{HB}} + c_w^2 c_{\mathrm{HW}} + s_w c_w c_{\mathrm{HWB}}\right),}$$

$$g_2^{Z\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{HW}} - c_{\mathrm{HB}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{HWB}}\right),$$

$$g_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{HB}} + s_w^2 c_{\mathrm{HW}} - s_w c_w c_{\mathrm{HWB}}\right),$$

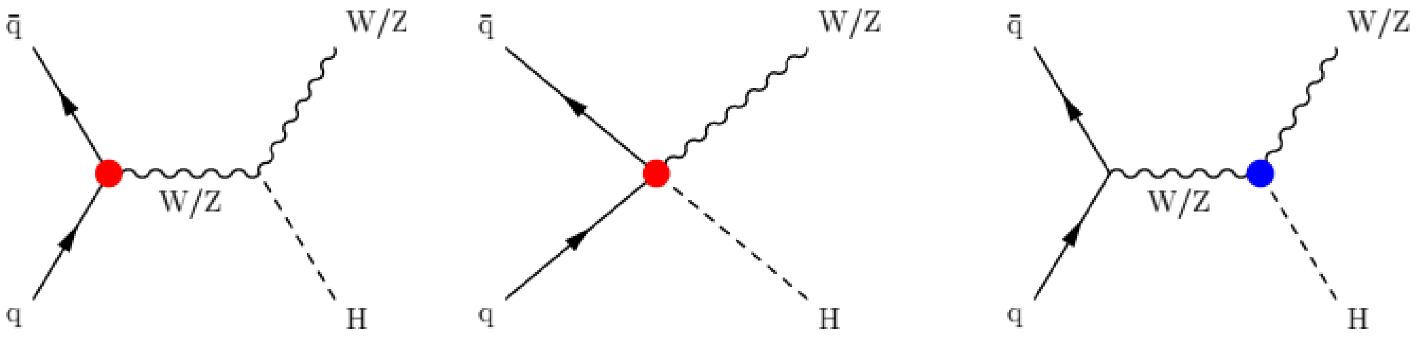
$$c_w = \cos\theta_{\mathrm{W}}$$

$$\boxed{g_4^{ZZ} = \tilde{g}_2^{ZZ} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{H\widetilde{B}}} + c_w^2 c_{\mathrm{H\widetilde{W}}} + s_w c_w c_{\mathrm{H\widetilde{W}B}}\right),}$$

$$g_4^{Z\gamma} = \tilde{g}_2^{Z\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{H\widetilde{W}}} - c_{\mathrm{H\widetilde{B}}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{H\widetilde{W}B}}\right),$$

$$g_4^{\gamma\gamma} = \tilde{g}_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{H\widetilde{B}}} + s_w^2 c_{\mathrm{H\widetilde{W}}} - s_w c_w c_{\mathrm{H\widetilde{W}B}}\right).$$

EFT effects in V associated H production



Rotation to mass eigenstate basis

Current operators

$\mathcal{O}_{\mathrm{Hq}}^{(1)}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c_{\mathrm{Hq}}^{(1)}$
$\mathcal{O}_{\mathrm{Hq}}^{(3)}$	$i\mathrm{H}^{\dagger}\sigma^{a}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{q}}_{\mathrm{L}}\sigma^{a}\gamma^{\mu}\mathrm{q}_{\mathrm{L}}$	$c_{\mathrm{Hq}}^{(3)}$
$\mathcal{O}_{\mathrm{Hu}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{u}}_{\mathrm{R}}\gamma^{\mu}\mathrm{u}_{\mathrm{R}}$	c_{Hu}
$\mathcal{O}_{\mathrm{Hd}}$	$i\mathrm{H}^{\dagger}\overleftrightarrow{D}_{\mu}\mathrm{H}\bar{\mathrm{d}}_{\mathrm{R}}\gamma^{\mu}\mathrm{d}_{\mathrm{R}}$	c_{Hd}

Gauge coupling operators

$\mathcal{O}_{\mathrm{HWB}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}\mathrm{W}^{a}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HWB}
$\mathcal{O}_{\mathrm{HW}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\mathrm{W}^{a\mu\nu}$	c_{HW}
$\mathcal{O}_{\mathrm{HB}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\mathrm{B}^{\mu\nu}$	c_{HB}
$\mathcal{O}_{\mathrm{H\widetilde{W}B}}$	$\mathrm{H}^{\dagger}\sigma^{a}\mathrm{H}\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{W}B}}$
$\mathcal{O}_{\mathrm{H\widetilde{W}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{W}^{a}_{\mu\nu}\widetilde{\mathrm{W}}^{a\mu\nu}$	$c_{\mathrm{H\widetilde{W}}}$
$\mathcal{O}_{\mathrm{H\widetilde{B}}}$	$(\mathrm{H}^{\dagger}\mathrm{H})\,\mathrm{B}_{\mu\nu}\widetilde{\mathrm{B}}^{\mu\nu}$	$c_{\mathrm{H\widetilde{B}}}$

$$\boxed{g_2^{ZZ} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{HB}} + c_w^2 c_{\mathrm{HW}} + s_w c_w c_{\mathrm{HWB}}\right),}$$

$$g_2^{Z\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{HW}} - c_{\mathrm{HB}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{HWB}}\right),$$

$$g_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{HB}} + s_w^2 c_{\mathrm{HW}} - s_w c_w c_{\mathrm{HWB}}\right),$$

$$c_w = \cos\theta_{\mathrm{W}}$$

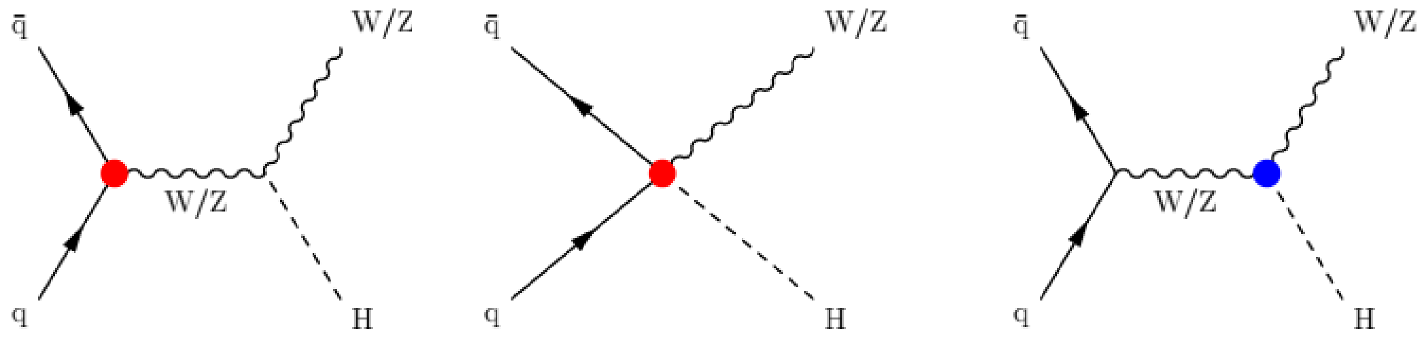
$$\boxed{g_4^{ZZ} = \tilde{g}_2^{ZZ} = -2\frac{v^2}{\Lambda^2}\left(s_w^2 c_{\mathrm{H\widetilde{B}}} + c_w^2 c_{\mathrm{H\widetilde{W}}} + s_w c_w c_{\mathrm{H\widetilde{W}B}}\right),}$$

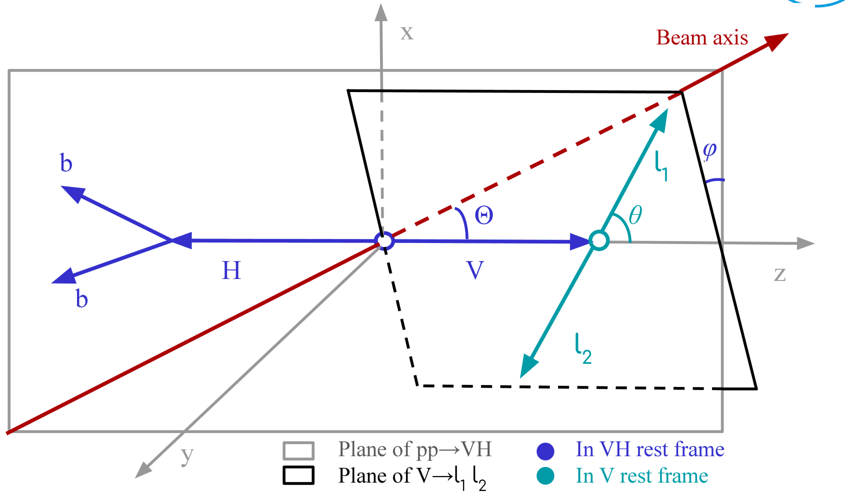
$$g_4^{Z\gamma} = \tilde{g}_2^{Z\gamma} = -2\frac{v^2}{\Lambda^2}\left(s_w c_w (c_{\mathrm{H\widetilde{W}}} - c_{\mathrm{H\widetilde{B}}}) + \frac{1}{2}(s_w^2 - c_w^2) c_{\mathrm{H\widetilde{W}B}}\right),$$

$$g_4^{\gamma\gamma} = \tilde{g}_2^{\gamma\gamma} = -2\frac{v^2}{\Lambda^2}\left(c_w^2 c_{\mathrm{H\widetilde{B}}} + s_w^2 c_{\mathrm{H\widetilde{W}}} - s_w c_w c_{\mathrm{H\widetilde{W}B}}\right).$$

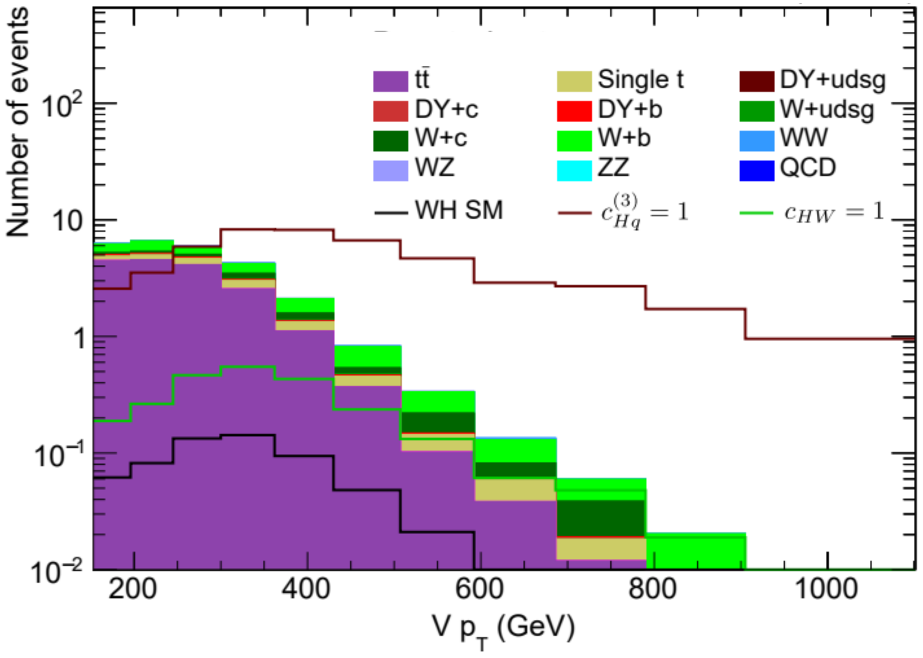
Coefficients targeted in measurement: $c_{\mathrm{Hq}}^{(1)},\ c_{\mathrm{Hq}}^{(3)},\ c_{\mathrm{Hu}},\ c_{\mathrm{Hd}},\ g_2^{ZZ},\ g_4^{ZZ}$

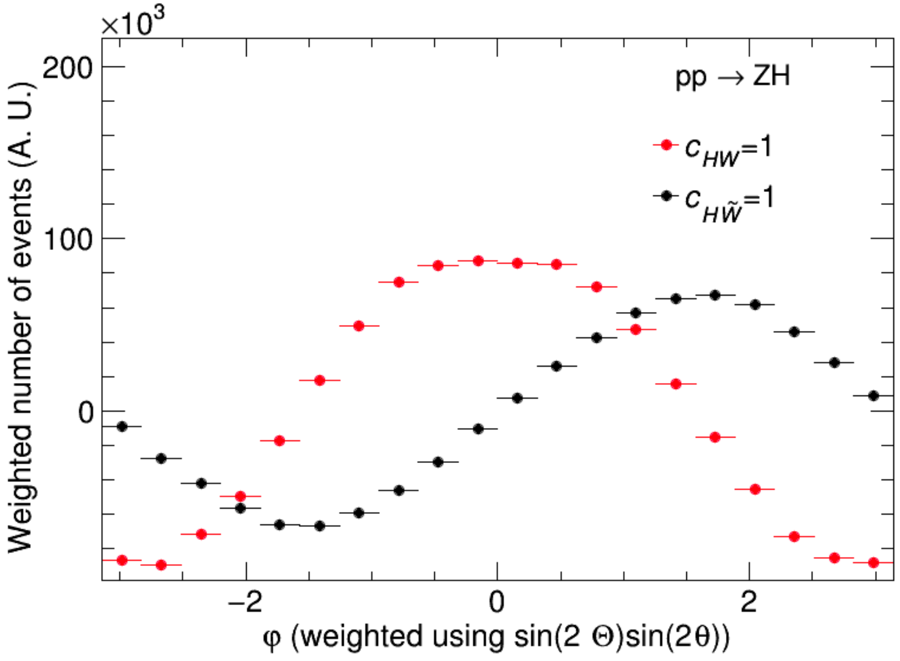
EFT effects in V associated H production





Use of angular variables followed from Banerjee, Gupta, Reiness, Seth, Spannowsky (2019)





EFT effects:

Changing energy spectra

+

Modifying angular correlation

Signal simulation strategy

Polynomial parameterization

$$\boxed{\mathcal{M}_{\mathrm{SMEFT}} = \mathcal{M}_{\mathrm{SM}} + \sum_i \frac{\mathrm{c}_i}{\Lambda^2}\mathcal{M}_{6,\mathrm{i}}}$$

$$\begin{aligned}\sigma &\sim \left|\mathcal{M}_{\mathrm{SMEFT}}\right|^2 \\ &\sim \left|\mathcal{M}_{\mathrm{SM}}\right|^2 + \sum_i \frac{\mathrm{c}_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}_{\mathrm{SM}}^{\dagger}\mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{\mathrm{c}_i^2}{\Lambda^4}\left|\mathcal{M}_{6,\mathrm{i}}\right|^2 + \sum_i \sum_{j,j>i} \frac{\mathrm{c}_i \mathrm{c}_j}{\Lambda^4}\mathcal{M}_{6,\mathrm{i}}\mathcal{M}_{6,\mathrm{j}}\end{aligned}$$

σ is a quadratic function of coefficients !

Signal simulation strategy

Polynomial parameterization

$$\mathcal{M}_{\mathrm{SMEFT}} = \mathcal{M}_{\mathrm{SM}} + \sum_i \frac{\mathrm{c}_i}{\Lambda^2}\mathcal{M}_{6,\mathrm{i}}$$

$$\sigma \sim |\mathcal{M}_{\mathrm{SMEFT}}|^2$$
$$\sim |\mathcal{M}_{\mathrm{SM}}|^2 + \sum_i \frac{\mathrm{c}_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}_{\mathrm{SM}}^\dagger \mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{\mathrm{c}_i^2}{\Lambda^4}|\mathcal{M}_{6,\mathrm{i}}|^2 + \sum_i \sum_{j,j>i} \frac{\mathrm{c}_i \mathrm{c}_j}{\Lambda^4}\mathcal{M}_{6,\mathrm{i}}\mathcal{M}_{6,\mathrm{j}}$$

σ is a quadratic function of coefficients !

# of signal samples (for 'n' coefficients): N(n) =1 + n + n(n+1)/2 ← Sufficient

Signal simulation strategy

Polynomial parameterization

$$\mathcal{M}_{\mathrm{SMEFT}} = \mathcal{M}_{\mathrm{SM}} + \sum_i \frac{\mathrm{c}_i}{\Lambda^2}\mathcal{M}_{6,\mathrm{i}}$$

$$\sigma \sim |\mathcal{M}_{\mathrm{SMEFT}}|^2$$

$$\sim |\mathcal{M}_{\mathrm{SM}}|^2 + \sum_i \frac{\mathrm{c}_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}^{\dagger}_{\mathrm{SM}}\mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{\mathrm{c}_i^2}{\Lambda^4}|\mathcal{M}_{6,\mathrm{i}}|^2 + \sum_i \sum_{j,j>i} \frac{\mathrm{c}_i \mathrm{c}_j}{\Lambda^4}\mathcal{M}_{6,\mathrm{i}}\mathcal{M}_{6,\mathrm{j}}$$

σ is a quadratic function of coefficients !

# of signal samples (for ‘n’ coefficients): N(n) =1 + n + n(n+1)/2 ← Sufficient

Possible to encode SMEFT prediction in event weights

$$\omega = \frac{|\mathcal{M}_{SMEFT}(\mathrm{c} = c_1)|^2}{|\mathcal{M}_{SMEFT}(\mathrm{c} = c_0)|^2}$$

Signal simulation strategy

Polynomial parameterization

$$\boxed{\mathcal{M}_{\mathrm{SMEFT}} = \mathcal{M}_{\mathrm{SM}} + \sum_i \frac{c_i}{\Lambda^2}\mathcal{M}_{6,\mathrm{i}}}$$

$$\sigma \sim |\mathcal{M}_{\mathrm{SMEFT}}|^2$$

$$\sim |\mathcal{M}_{\mathrm{SM}}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}_{\mathrm{SM}}^{\dagger}\mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,\mathrm{i}}|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,\mathrm{i}}\mathcal{M}_{6,\mathrm{j}}$$

σ is a quadratic function of coefficients !

# of signal samples (for 'n' coefficients): N(n) =1 + n + n(n+1)/2 ← Sufficient

Possible to encode SMEFT prediction in event weights

$$\omega = \frac{|\mathcal{M}_{SMEFT}(c = c_1)|^2}{|\mathcal{M}_{SMEFT}(c = c_0)|^2}$$

$$\omega(\boldsymbol{z}|\boldsymbol{c}) \sim \frac{d\sigma}{d\boldsymbol{z}} = \mathrm{Const}(\boldsymbol{z}) + \mathrm{LIN}_a(\boldsymbol{z})c_a + \frac{1}{2}\mathrm{QUAD}_{ab}(\boldsymbol{z})c_a c_b$$

Signal simulation strategy

Polynomial parameterization

$$\boxed{\mathcal{M}_{\mathrm{SMEFT}} = \mathcal{M}_{\mathrm{SM}} + \sum_i \frac{\mathrm{c}_i}{\Lambda^2} \mathcal{M}_{6,\mathrm{i}}}$$

$$\sigma \sim |\mathcal{M}_{\mathrm{SMEFT}}|^2$$

$$\sim |\mathcal{M}_{\mathrm{SM}}|^2 + \sum_i \frac{\mathrm{c}_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}_{\mathrm{SM}}^{\dagger} \mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{\mathrm{c}_i^2}{\Lambda^4} |\mathcal{M}_{6,\mathrm{i}}|^2 + \sum_i \sum_{j,j>i} \frac{\mathrm{c}_i \mathrm{c}_j}{\Lambda^4} \mathcal{M}_{6,\mathrm{i}} \mathcal{M}_{6,\mathrm{j}}$$

σ is a quadratic function of coefficients !

\# of signal samples (for ‘n’ coefficients): N(n) =1 + n + n(n+1)/2 ← Sufficient

Possible to encode SMEFT prediction in event weights

$$\omega = \frac{|\mathcal{M}_{SMEFT}(\mathrm{c} = c_1)|^2}{|\mathcal{M}_{SMEFT}(\mathrm{c} = c_0)|^2}$$

$$\omega(\boldsymbol{z}|\boldsymbol{c}) \sim \frac{d\sigma}{dz} = \mathrm{Const}(\boldsymbol{z}) + \mathrm{LIN}_a(\boldsymbol{z}) c_a + \frac{1}{2} \mathrm{QUAD}_{ab}(\boldsymbol{z}) c_a c_b$$

Store N(n) weights per event
→ obtain EFT prediction for any coefficient value

Signal simulation strategy

Polynomial parameterization

$$\mathcal{M}_{\mathrm{SMEFT}} = \mathcal{M}_{\mathrm{SM}} + \sum_i \frac{c_i}{\Lambda^2} \mathcal{M}_{6,\mathrm{i}}$$

$$\sigma \sim |\mathcal{M}_{\mathrm{SMEFT}}|^2$$
$$\sim |\mathcal{M}_{\mathrm{SM}}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}_{\mathrm{SM}}^{\dagger}\mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,\mathrm{i}}|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4} \mathcal{M}_{6,\mathrm{i}} \mathcal{M}_{6,\mathrm{j}}$$

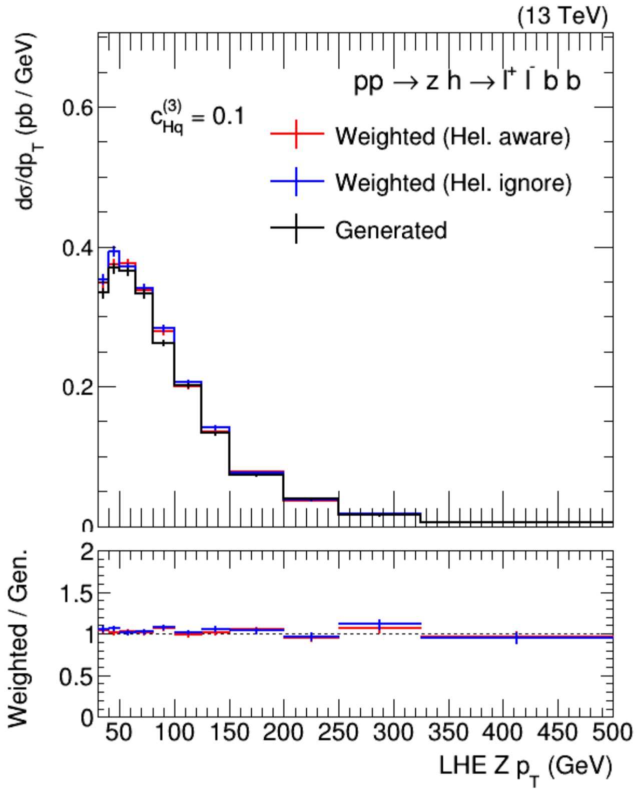
σ is a quadratic function of coefficients !

# of signal samples (for 'n' coefficients): N(n) =1 + n + n(n+1)/2 ← Sufficient

Possible to encode SMEFT prediction in event weights

$$\omega = \frac{|\mathcal{M}_{SMEFT}(\mathrm{c} = c_1)|^2}{|\mathcal{M}_{SMEFT}(\mathrm{c} = c_0)|^2}$$

$$\omega(\boldsymbol{z}|\boldsymbol{c}) \sim \frac{d\sigma}{d\boldsymbol{z}} = \mathrm{Const}(\boldsymbol{z}) + \mathrm{LIN}_a(\boldsymbol{z})c_a + \frac{1}{2}\mathrm{QUAD}_{ab}(\boldsymbol{z})c_a c_b$$



Store N(n) weights per event

→ obtain EFT prediction for any coefficient value

Signal simulation strategy

Polynomial parameterization

$$\mathcal{M}_{\text{SMEFT}} = \mathcal{M}_{\text{SM}} + \sum_i \frac{c_i}{\Lambda^2}\mathcal{M}_{6,i}$$

$$\sigma \sim |\mathcal{M}_{\text{SMEFT}}|^2$$

$$\sim |\mathcal{M}_{\text{SM}}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2\text{Re}(\mathcal{M}_{\text{SM}}^\dagger \mathcal{M}_{6,i}) + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,i}|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,i}\mathcal{M}_{6,j}$$

σ is a quadratic function of coefficients !

# of signal samples (for 'n' coefficients): N(n) =1 + n + n(n+1)/2 ← Sufficient

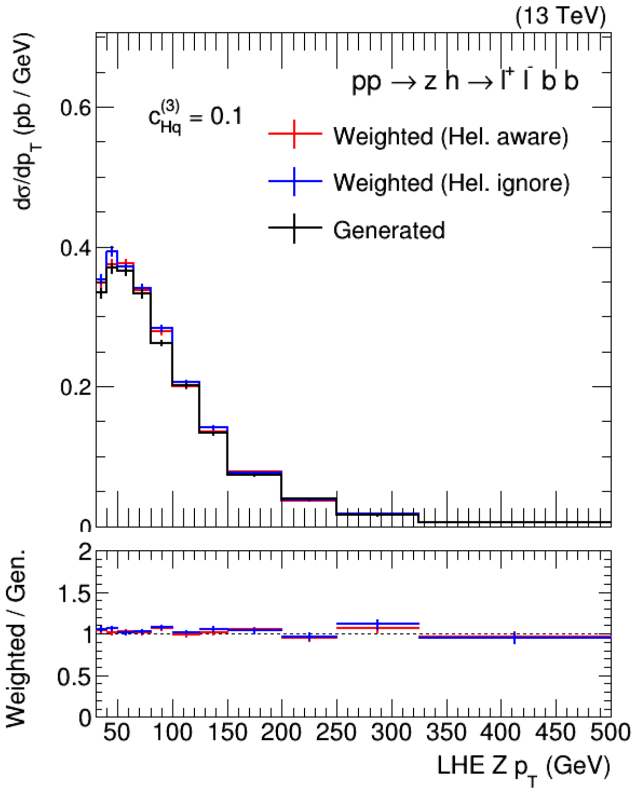
Possible to encode SMEFT prediction in event weights

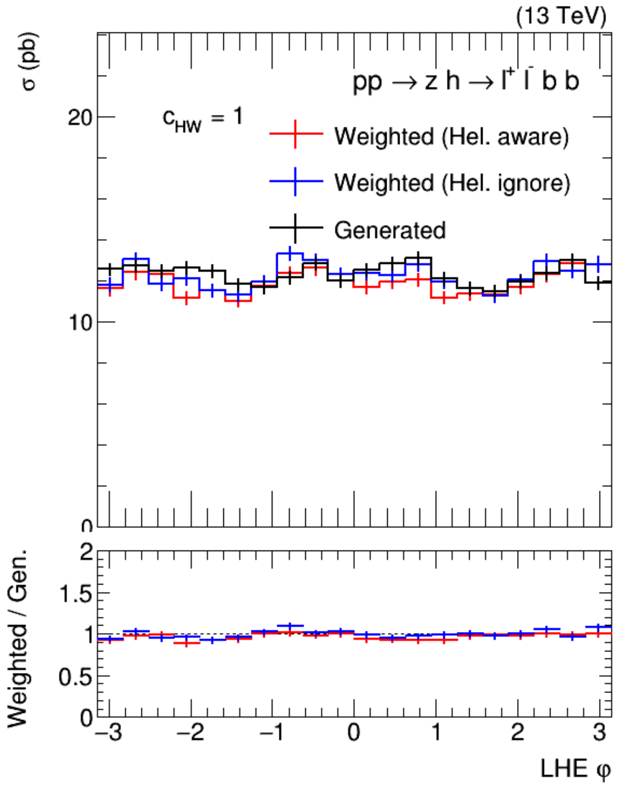
$$\omega = \frac{|\mathcal{M}_{SMEFT}(\text{c} = c_1)|^2}{|\mathcal{M}_{SMEFT}(\text{c} = c_0)|^2}$$

$$\omega(\boldsymbol{z}|\boldsymbol{c}) \sim \frac{d\sigma}{d\boldsymbol{z}} = \text{Const}(\boldsymbol{z}) + \text{LIN}_a(\boldsymbol{z})c_a + \frac{1}{2}\text{QUAD}_{ab}(\boldsymbol{z})c_a c_b$$

Store N(n) weights per event

→ obtain EFT prediction for any coefficient value





Signal simulation strategy

Polynomial parameterization

$$\mathcal{M}_{\rm SMEFT} = \mathcal{M}_{\rm SM} + \sum_i \frac{c_i}{\Lambda^2}\mathcal{M}_{6,i}$$

$$\begin{aligned}\sigma &\sim |\mathcal{M}_{\rm SMEFT}|^2 \\ &\sim |\mathcal{M}_{\rm SM}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2{\rm Re}(\mathcal{M}^{\dagger}_{\rm SM}\mathcal{M}_{6,i}) + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,i}|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,i}\mathcal{M}_{6,j}\end{aligned}$$

σ is a quadratic function of coefficients !

# of signal samples (for ‘n’ coefficients): N(n) =1 + n + n(n+1)/2 ← Sufficient

Possible to encode SMEFT prediction in event weights

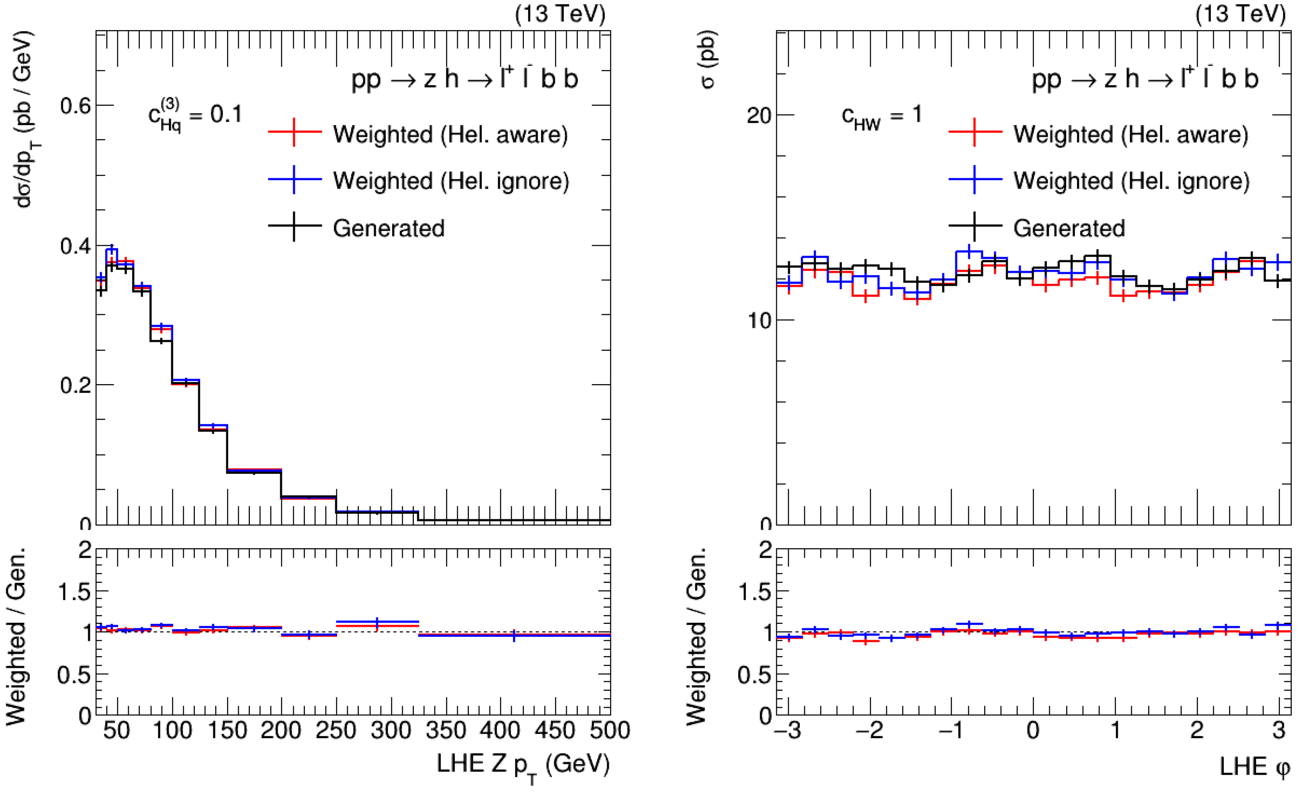
$$\omega = \frac{|\mathcal{M}_{SMEFT}(c = c_1)|^2}{|\mathcal{M}_{SMEFT}(c = c_0)|^2}$$

$$\omega(\boldsymbol{z}|\boldsymbol{c}) \sim \frac{d\sigma}{d\boldsymbol{z}} = {\rm Const}(\boldsymbol{z}) + {\rm LIN}_a(\boldsymbol{z})c_a + \frac{1}{2}{\rm QUAD}_{ab}(\boldsymbol{z})c_a c_b$$

Store N(n) weights per event

→ obtain EFT prediction for any coefficient value

SciPost Phys.Comm.Rep. (2024) 4



Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z) \left(z - f(\boldsymbol{x})\right)^2$$

$$0 \rightarrow \text{SM}, \;\; 1 \rightarrow \theta$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z) \left(z - f(\boldsymbol{x})\right)^2$$

$$0 \to \text{SM}, \; 1 \to \theta$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z) \, (z - f(\boldsymbol{x}))^2 \xrightarrow{\text{Minimizing L}} f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

$$0 \to \mathrm{SM}, \; 1 \to \theta$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int d\boldsymbol{x} \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2 \xrightarrow{\text{Minimizing L}} f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

$$0 \to \mathrm{SM},\ 1 \to \theta$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})}$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int d\boldsymbol{x} \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2 \xrightarrow{\text{Minimizing L}} f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

$$0 \to \mathrm{SM},\ 1 \to \theta$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

$$0 \rightarrow \text{SM},\ 1 \rightarrow \theta$$

$$\xrightarrow{\text{Minimizing L}}$$

$$f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\text{SM})}{p(\boldsymbol{x}|\text{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\text{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\text{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$\boldsymbol{x} \leftarrow$ observable

Observable: likelihood-free inference

Likelihood ratio trick in classification

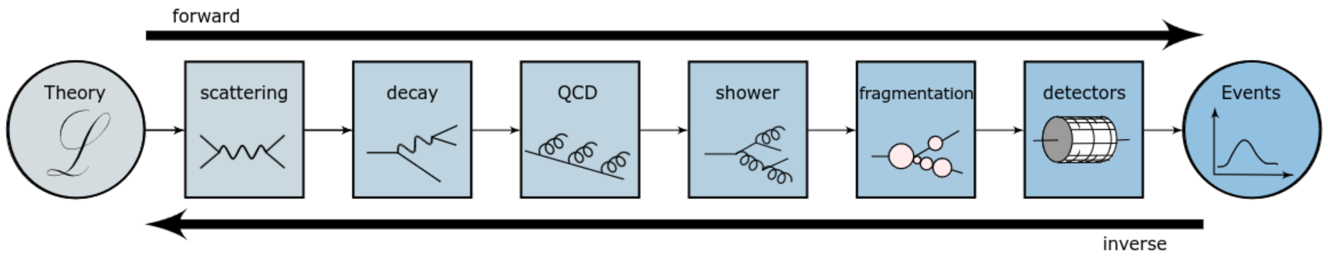
$$L = \int d\boldsymbol{x} \sum_{z\in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2 \xrightarrow{\text{Minimizing L}} f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\text{SM})}{p(\boldsymbol{x}|\text{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\text{SM})} r(\boldsymbol{x})}$$

$$0 \to \text{SM},\ 1 \to \theta$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\text{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$\boldsymbol{x} \leftarrow$ observable



Picture taken from Plehn, Butter, Dillon, Krause (2022)

Observable: likelihood-free inference

Likelihood ratio trick in classification

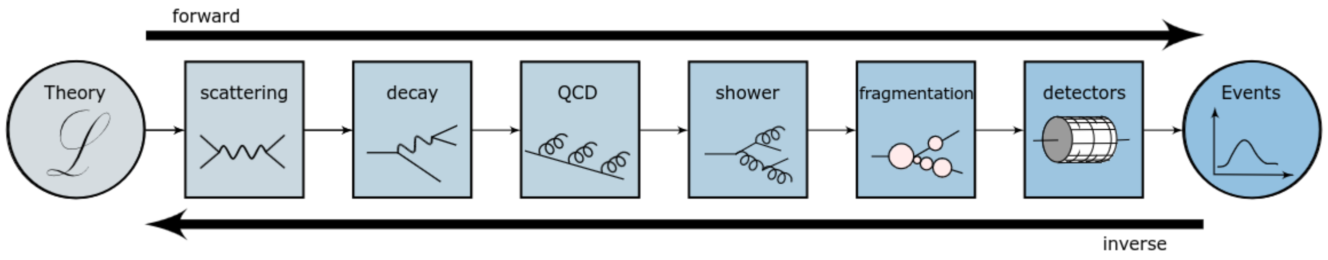
$$L = \int d\boldsymbol{x} \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2 \xrightarrow{\text{Minimizing L}} f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

$$0 \rightarrow \mathrm{SM},\ 1 \rightarrow \theta$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$\boldsymbol{x} \leftarrow$ observable



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int p(\boldsymbol{x}|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}p(z|\boldsymbol{\theta})dz$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int d\boldsymbol{x} \sum_{z\in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

$$0 \to \mathrm{SM},\; 1 \to \theta$$

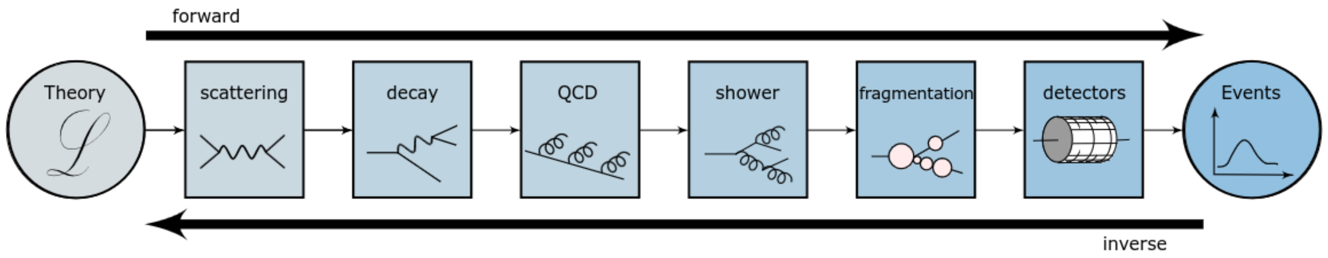
Minimizing L →

$$f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$\boldsymbol{x} \leftarrow$ observable



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(x|\boldsymbol{\theta}) = \int\int\int p(x|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}p(z|\boldsymbol{\theta})dz$$

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta})d\boldsymbol{z}$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

$$0 \to \mathrm{SM},\ 1 \to \theta$$

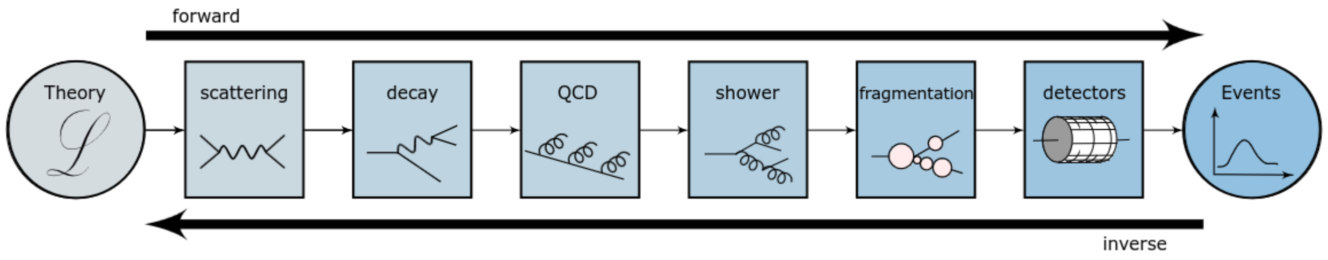
Minimizing L

$$f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$$\boldsymbol{x} \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|\boldsymbol{z})dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}}\,p(\boldsymbol{z}|\boldsymbol{\theta})d\boldsymbol{z}$$

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\,p(\boldsymbol{z}|\boldsymbol{\theta})d\boldsymbol{z}$$

intractable

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

$$0 \rightarrow \mathrm{SM},\ 1 \rightarrow \theta$$

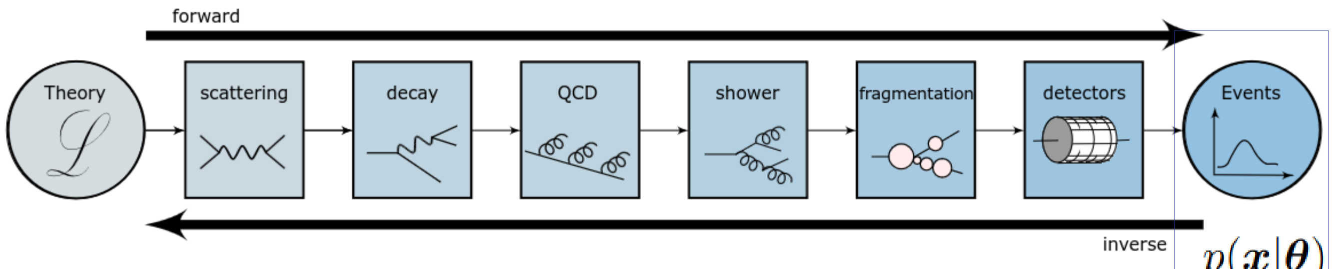
Minimizing L

$$f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$\boldsymbol{x} \leftarrow$ observable



$p(\boldsymbol{x}|\boldsymbol{\theta})$

Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}} p(z|\boldsymbol{\theta})dz$$

intractable

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})} p(\boldsymbol{z}|\boldsymbol{\theta})d\boldsymbol{z}$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(x, z)\,(z - f(x))^2$$

$$0 \to \mathrm{SM}, \; 1 \to \theta$$

Minimizing L

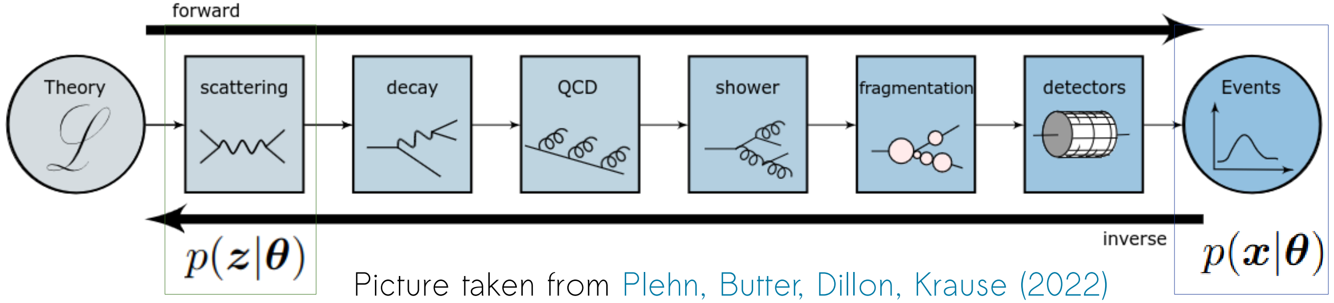
$$\xrightarrow{}$$

$$f^*(x) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$\boldsymbol{x} \leftarrow$ observable



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|\boldsymbol{z})dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}} p(\boldsymbol{z}|\boldsymbol{\theta})d\boldsymbol{z}$$

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\boxed{p(\boldsymbol{z}|\boldsymbol{\theta})}d\boldsymbol{z}$$

intractable

tractable

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int d\boldsymbol{x} \sum_{z\in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

$$0 \rightarrow \mathrm{SM},\ 1 \rightarrow \theta$$

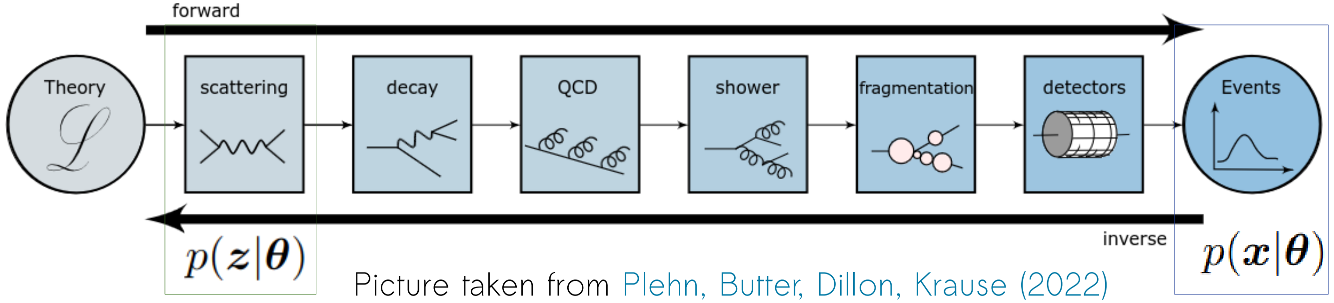
$$\xrightarrow{\text{Minimizing L}}$$

$$f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$$\boldsymbol{x} \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}}\,p(z|\boldsymbol{\theta})dz$$

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\boxed{p(\boldsymbol{z}|\boldsymbol{\theta})}dz$$

intractable
tractable

Inverse problem: Estimate θ from p(x)

Observable: likelihood-free inference

Likelihood ratio trick in classification

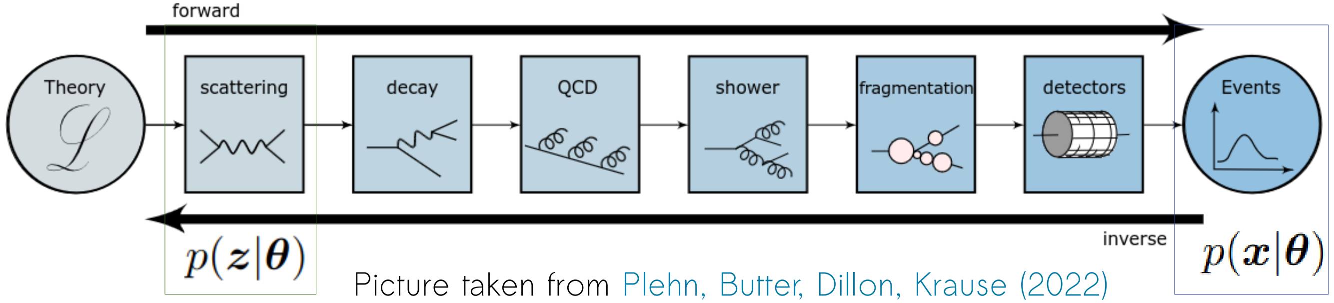
$$L = \int dx \sum_{z\in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2 \xrightarrow{\text{Minimizing L}} f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\text{SM})}{p(\boldsymbol{x}|\text{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\text{SM})} r(\boldsymbol{x})}$$

$$0 \to \text{SM},\ 1 \to \theta$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\text{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$$\boldsymbol{x} \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\text{Det}})p(z_{\text{Det}}|z_{\text{Had}})p(z_{\text{Had}}|z_{\text{PS}})p(z_{\text{PS}}|z)dz_{\text{Det}}dz_{\text{Had}}dz_{\text{PS}}}\,p(z|\boldsymbol{\theta})dz$$

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\boxed{p(\boldsymbol{z}|\boldsymbol{\theta})}dz$$

intractable
tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z\in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

$$0 \rightarrow \mathrm{SM},\ 1 \rightarrow \theta$$

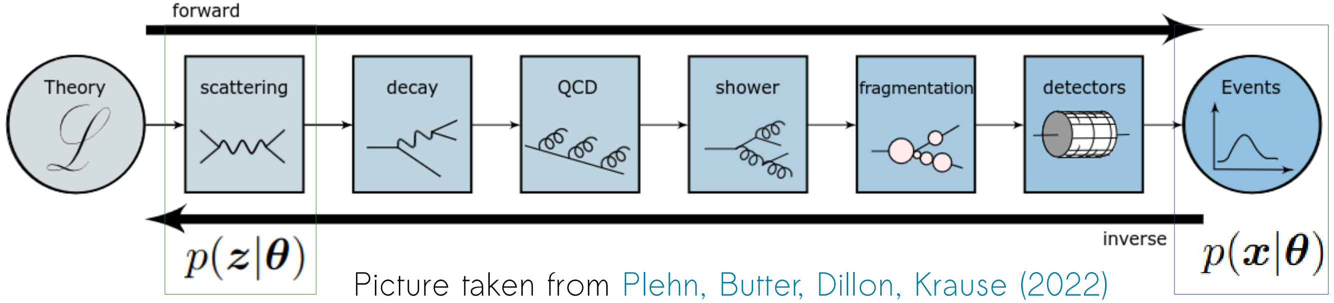
Minimizing L

$$f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$$\boldsymbol{x} \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|\boldsymbol{z})dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}}\,p(\boldsymbol{z}|\boldsymbol{\theta})d\boldsymbol{z}$$

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\boxed{p(\boldsymbol{z}|\boldsymbol{\theta})}d\boldsymbol{z}$$

intractable

tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

$$R(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0) = \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{z}|\boldsymbol{\theta}_0)}$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

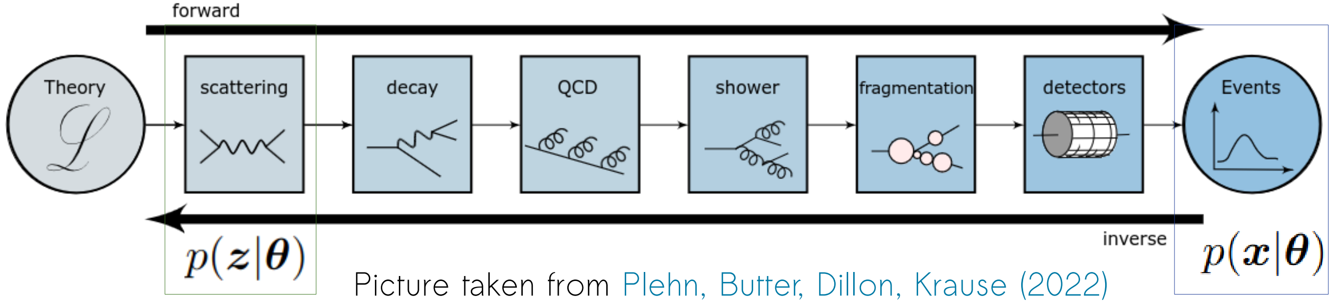
$$0 \to \text{SM},\ 1 \to \theta$$

$$\xrightarrow{\text{Minimizing L}} \quad f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\text{SM})}{p(\boldsymbol{x}|\text{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\text{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\text{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$$\boldsymbol{x} \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\text{Det}})p(z_{\text{Det}}|z_{\text{Had}})p(z_{\text{Had}}|z_{\text{PS}})p(z_{\text{PS}}|z)dz_{\text{Det}}dz_{\text{Had}}dz_{\text{PS}}}\,p(z|\boldsymbol{\theta})dz$$

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\boxed{p(\boldsymbol{z}|\boldsymbol{\theta})}dz$$

intractable

tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

$$R(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0) = \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{z}|\boldsymbol{\theta}_0)}$$

$$L[\hat{F}] = \int dx dz p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)|F(\boldsymbol{x}, \boldsymbol{z}) - \hat{F}(x)|^2$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z\in 0,1} p(x,z)\,(z - f(x))^2$$

$$0 \to \mathrm{SM},\ 1 \to \theta$$

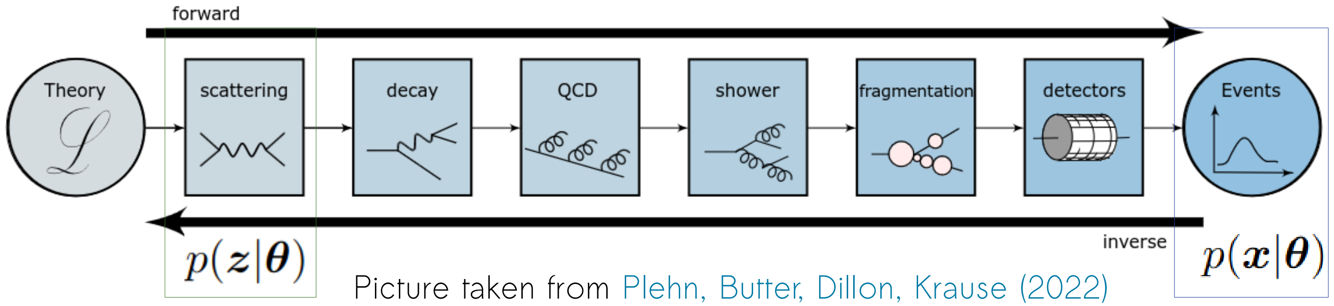
Minimizing L

$$f^*(x) = \frac{p(x|\mathrm{SM})}{p(x|\mathrm{SM}) + p(x|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(x)}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(x) = \frac{p(x|\theta)}{p(x|\mathrm{SM})} \longrightarrow R(x|\theta_1, \theta_0)$$

$$x \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(x|\theta) = \int\int\int \boxed{p(x|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}}p(z|\theta)dz$$

$$\boxed{p(x|\theta)} = \int \boxed{p(x|z)}\boxed{p(z|\theta)}dz$$

intractable
tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

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

$$L[\hat{F}] = \int dxdz p(x,z|\theta_0)|F(x,z) - \hat{F}(x)|^2$$

$$F(x,z) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} R(x,z) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(x,z|\theta_1)}{p(x,z|\theta_0)}$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

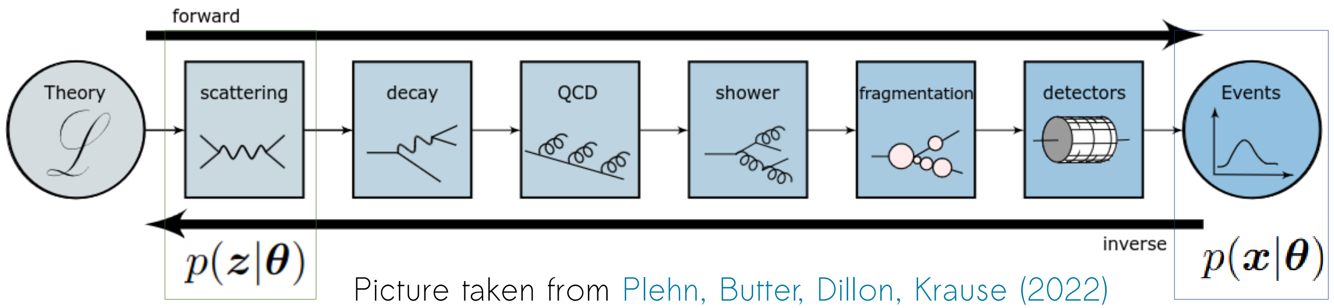
$$L = \int dx \sum_{z\in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2 \xrightarrow{\text{Minimizing L}} f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

$$0 \to \mathrm{SM},\; 1 \to \theta$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$$\boldsymbol{x} \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}} p(z|\boldsymbol{\theta})dz$$

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\boxed{p(\boldsymbol{z}|\boldsymbol{\theta})}dz$$

intractable

tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

$$R(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0) = \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{z}|\boldsymbol{\theta}_0)}$$

$$L[\hat{F}] = \int dx dz p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)|F(\boldsymbol{x}, \boldsymbol{z}) - \hat{F}(x)|^2$$

$$F(\boldsymbol{x}, \boldsymbol{z}) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} R(\boldsymbol{x}, \boldsymbol{z}) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)}$$

$$\hat{R}(\boldsymbol{x}) = \frac{\int dz p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0) \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(\boldsymbol{x},\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x},\boldsymbol{z}|\boldsymbol{\theta}_0)}}{\int dz p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(\boldsymbol{x}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}|\boldsymbol{\theta}_0)} = R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z\in 0,1} p(x,z)\,(z-f(x))^2$$

$$0 \to \mathrm{SM},\ 1 \to \theta$$

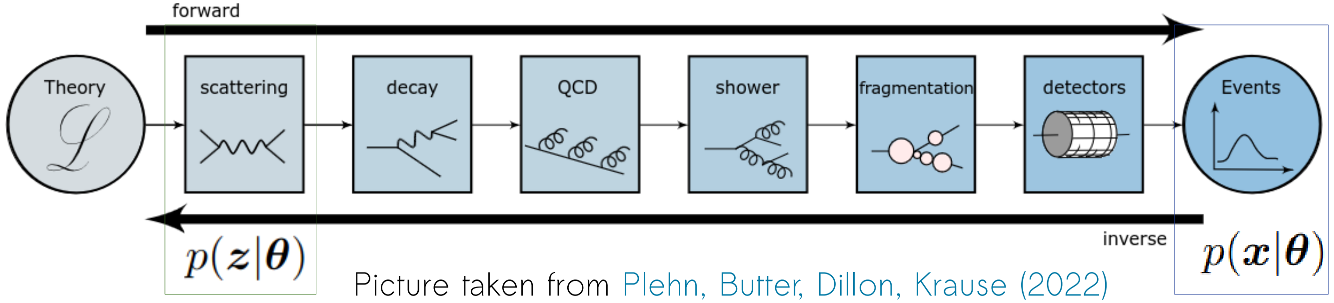
$$\xrightarrow{\text{Minimizing L}}$$

$$f^*(x) = \frac{p(x|\mathrm{SM})}{p(x|\mathrm{SM}) + p(x|\theta)} = \frac{1}{1+\frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(x)}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(x) = \frac{p(x|\theta)}{p(x|\mathrm{SM})} \longrightarrow R(x|\theta_1,\theta_0)$$

$$x \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(x|\theta) = \int\int\int \boxed{p(x|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}}p(z|\theta)dz$$

$$\boxed{p(x|\theta)} = \int \boxed{p(x|z)}\boxed{p(z|\theta)}dz$$

intractable

tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

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

$$L[\hat{F}] = \int dxdz p(x,z|\theta_0)|F(x,z) - \hat{F}(x)|^2$$

$$F(x,z) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} R(x,z) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(x,z|\theta_1)}{p(x,z|\theta_0)}$$

$$\hat{R}(x) = \frac{\int dz p(x,z|\theta_0)\frac{\sigma(\theta_1)}{\sigma(\theta_0)}\frac{p(x,z|\theta_1)}{p(x,z|\theta_0)}}{\int dz p(x,z|\theta_0)} = \frac{\sigma(\theta_1)}{\sigma(\theta_0)}\frac{p(x|\theta_1)}{p(x|\theta_0)} = R(x|\theta_1,\theta_0)$$

Likelihood-free / simulation-based inference

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

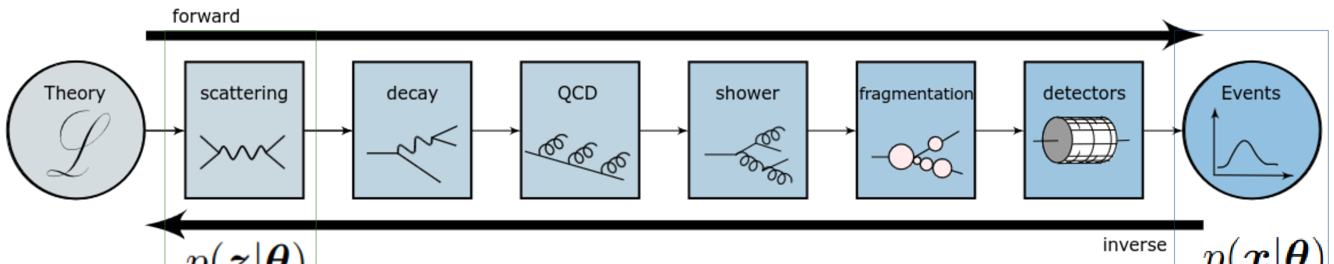
$$0 \to \mathrm{SM},\ 1 \to \theta$$

$$\xrightarrow{\text{Minimizing L}} \quad f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$$\boldsymbol{x} \leftarrow \text{observable}$$



$p(\boldsymbol{z}|\boldsymbol{\theta})$ $p(\boldsymbol{x}|\boldsymbol{\theta})$

Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(\boldsymbol{x}|\boldsymbol{\theta}) = \int\int\int \boxed{p(\boldsymbol{x}|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}}\,p(z|\boldsymbol{\theta})dz$$

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\boxed{p(\boldsymbol{z}|\boldsymbol{\theta})}dz$$

intractable

tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

$$R(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0) = \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{z}|\boldsymbol{\theta}_0)}$$

$$L[\hat{F}] = \int dxdzp(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)|F(\boldsymbol{x}, \boldsymbol{z}) - \hat{F}(x)|^2$$

$$F(\boldsymbol{x}, \boldsymbol{z}) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} R(\boldsymbol{x}, \boldsymbol{z}) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)}$$

$$\hat{R}(\boldsymbol{x}) = \frac{\int dzp(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)\frac{\sigma(\theta_1)}{\sigma(\theta_0)}\frac{p(\boldsymbol{x},\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x},\boldsymbol{z}|\boldsymbol{\theta}_0)}}{\int dzp(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{\sigma(\theta_1)}{\sigma(\theta_0)}\frac{p(\boldsymbol{x}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}|\boldsymbol{\theta}_0)} = R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

Likelihood-free / simulation-based inference

Boosted information tree (BIT)

Using decision trees to regress on learn likelihood ratio terms
→ very fast!

SC, N. Frohner, L. Lechner, R. Schoefbeck, D. Schwarz (2021)

Observable: likelihood-free inference

Likelihood ratio trick in classification

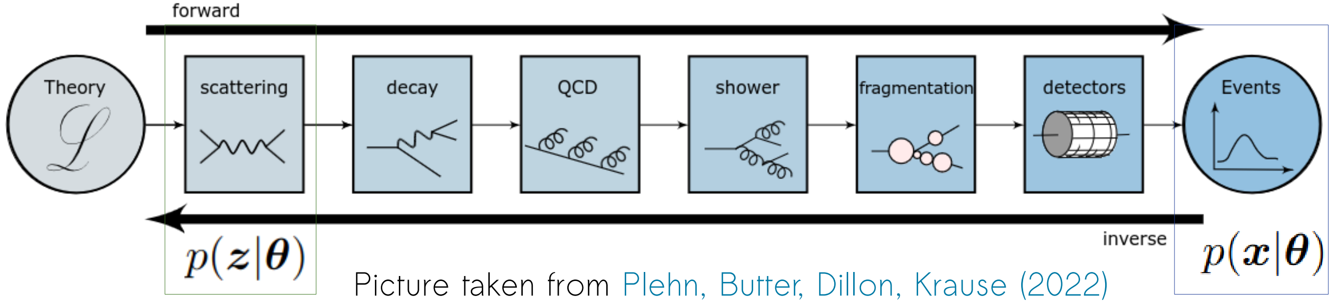
$$L = \int dx \sum_{z\in 0,1} p(x, z)\,(z - f(x))^2 \xrightarrow{\text{Minimizing L}} f^*(x) = \frac{p(x|\text{SM})}{p(x|\text{SM}) + p(x|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\text{SM})} r(x)}$$

$$0 \to \text{SM},\ 1 \to \theta$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(x) = \frac{p(x|\theta)}{p(x|\text{SM})} \longrightarrow R(x|\theta_1, \theta_0)$$

$$x \leftarrow \text{observable}$$



Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(x|\theta) = \int\int\int \boxed{p(x|z_{\text{Det}})p(z_{\text{Det}}|z_{\text{Had}})p(z_{\text{Had}}|z_{\text{PS}})p(z_{\text{PS}}|z)dz_{\text{Det}}dz_{\text{Had}}dz_{\text{PS}}}\,p(z|\theta)dz$$

$$\boxed{p(x|\theta)} = \int \boxed{p(x|z)}\boxed{p(z|\theta)}dz$$

intractable

tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

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

$$L[\hat{F}] = \int dxdz\,p(x, z|\theta_0)|F(x, z) - \hat{F}(x)|^2$$

$$F(x, z) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} R(x, z) = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(x, z|\theta_1)}{p(x, z|\theta_0)}$$

$$\hat{R}(x) = \frac{\int dz p(x, z|\theta_0) \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(x,z|\theta_1)}{p(x,z|\theta_0)}}{\int dz p(x, z|\theta_0)} = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(x|\theta_1)}{p(x|\theta_0)} = R(x|\theta_1, \theta_0)$$

Likelihood-free / simulation-based inference

Boosted information tree (BIT)

Using decision trees to regress on learn likelihood ratio terms
→ very fast! SC, N. Frohner, L. Lechner, R. Schoefbeck, D. Schwarz (2021)

\# of trainings = N + N + N(N-1)/2

Observable: likelihood-free inference

Likelihood ratio trick in classification

$$L = \int dx \sum_{z \in 0,1} p(\boldsymbol{x}, z)\,(z - f(\boldsymbol{x}))^2$$

$$0 \to \mathrm{SM},\ 1 \to \theta$$

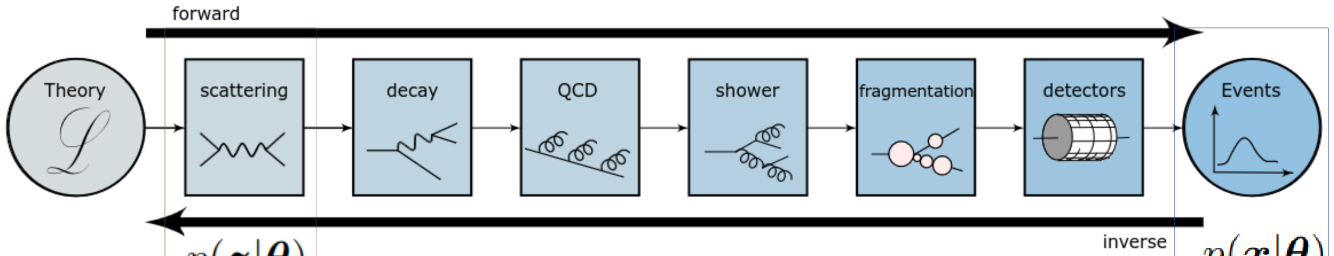
Minimizing L

$$f^*(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\mathrm{SM})}{p(\boldsymbol{x}|\mathrm{SM}) + p(\boldsymbol{x}|\theta)} = \frac{1}{1 + \frac{\sigma(\theta)}{\sigma(\mathrm{SM})} r(\boldsymbol{x})}$$

Optimal test statistic:
Likelihood ratio (LLR)

$$r(\boldsymbol{x}) = \frac{p(\boldsymbol{x}|\theta)}{p(\boldsymbol{x}|\mathrm{SM})} \longrightarrow R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

$$\boldsymbol{x} \leftarrow \text{observable}$$



$p(\boldsymbol{z}|\boldsymbol{\theta})$ $p(\boldsymbol{x}|\boldsymbol{\theta})$

Picture taken from Plehn, Butter, Dillon, Krause (2022)

$$p(x|\boldsymbol{\theta}) = \int\int\int \boxed{p(x|z_{\mathrm{Det}})p(z_{\mathrm{Det}}|z_{\mathrm{Had}})p(z_{\mathrm{Had}}|z_{\mathrm{PS}})p(z_{\mathrm{PS}}|z)dz_{\mathrm{Det}}dz_{\mathrm{Had}}dz_{\mathrm{PS}}}\,p(z|\boldsymbol{\theta})dz$$

$$\boxed{p(\boldsymbol{x}|\boldsymbol{\theta})} = \int \boxed{p(\boldsymbol{x}|\boldsymbol{z})}\boxed{p(\boldsymbol{z}|\boldsymbol{\theta})}dz$$

intractable
tractable

Inverse problem: Estimate θ from p(x)

LLR between two EFT hypotheses → learned by regressing on joint LLR

Brehmer, Cranmer, Louppe, Pavez (2018)

$$R(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0) = \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}|\boldsymbol{z})p(\boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{p(\boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{z}|\boldsymbol{\theta}_0)}$$

$$L[\hat{F}] = \int dx dz p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)|F(\boldsymbol{x}, \boldsymbol{z}) - \hat{F}(x)|^2$$

$$F(\boldsymbol{x}, \boldsymbol{z}) = \frac{\sigma(\boldsymbol{\theta}_1)}{\sigma(\boldsymbol{\theta}_0)} R(\boldsymbol{x}, \boldsymbol{z}) = \frac{\sigma(\boldsymbol{\theta}_1)}{\sigma(\boldsymbol{\theta}_0)} \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)}$$

$$\hat{R}(\boldsymbol{x}) = \frac{\int dz p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0) \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)}}{\int dz p(\boldsymbol{x}, \boldsymbol{z}|\boldsymbol{\theta}_0)} = \frac{\sigma(\theta_1)}{\sigma(\theta_0)} \frac{p(\boldsymbol{x}|\boldsymbol{\theta}_1)}{p(\boldsymbol{x}|\boldsymbol{\theta}_0)} = R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0)$$

Likelihood-free / simulation-based inference

Boosted information tree (BIT)

Using decision trees to regress on learn likelihood ratio terms
→ very fast! SC, N. Frohner, L. Lechner, R. Schoefbeck, D. Schwarz (2021)

# of trainings = N + N + N(N-1)/2

$$R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0) = 1 + (\theta_1 - \theta_0)_a \boxed{R_a(\boldsymbol{x})} + \frac{1}{2}(\theta_1 - \theta_0)_a(\theta_1 - \theta_0)_b \boxed{R_{a,b}(\boldsymbol{x})}$$

Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

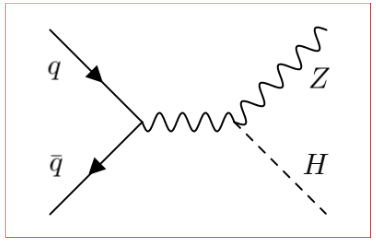
Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

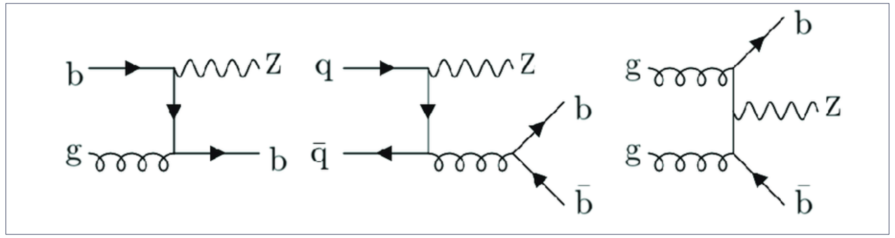
Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Signal



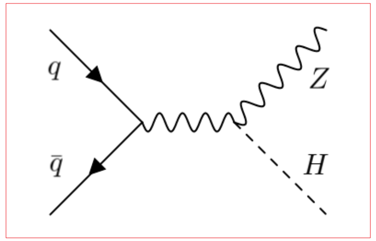
Background



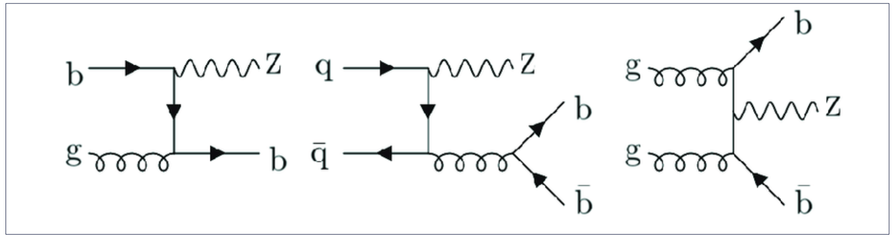
Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Signal



Background

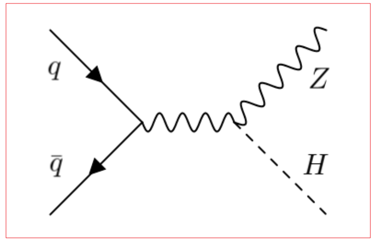


Traditional approach

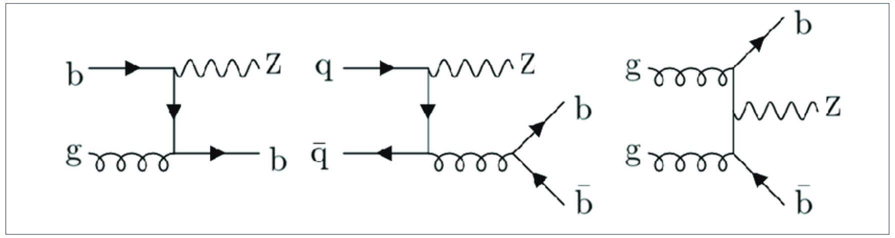
Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

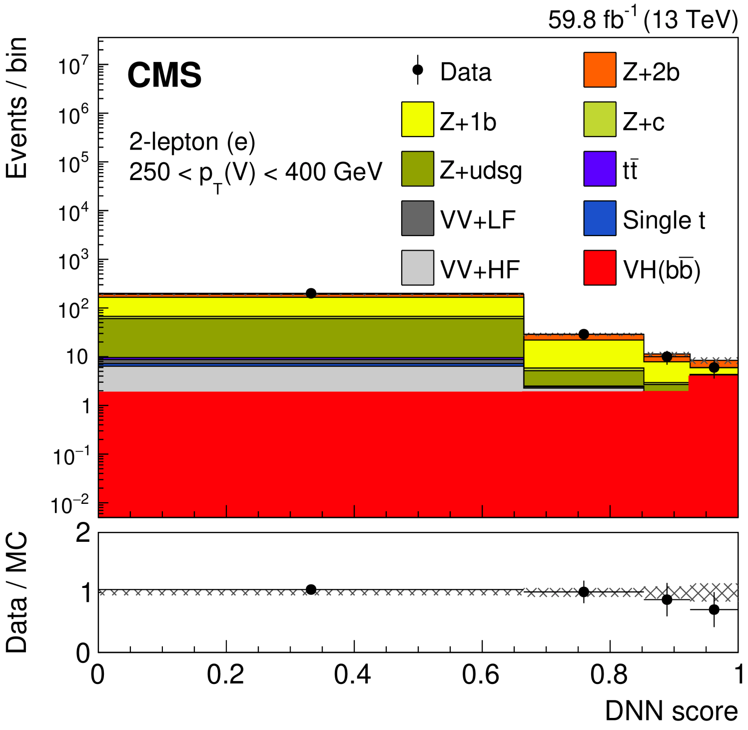
Signal



Background



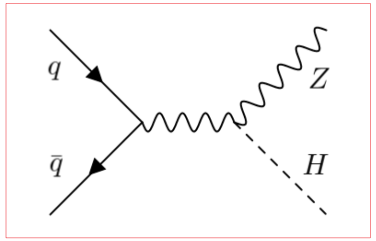
Traditional approach



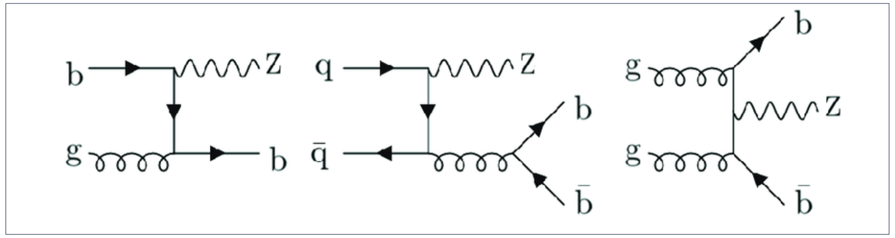
Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

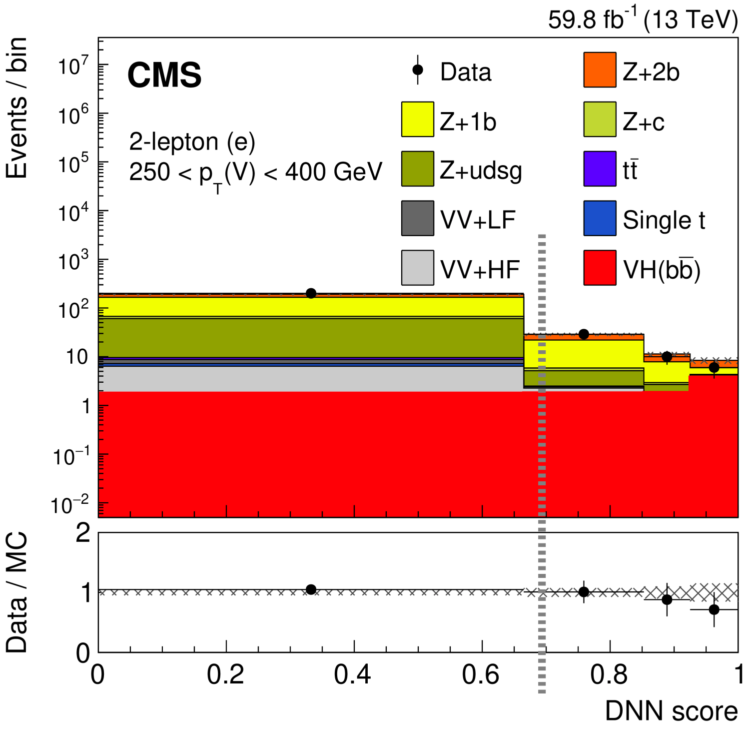
Signal



Background



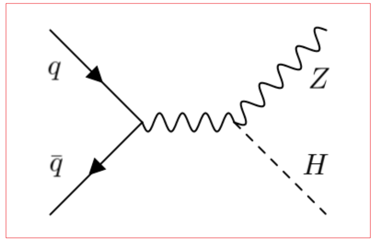
Traditional approach



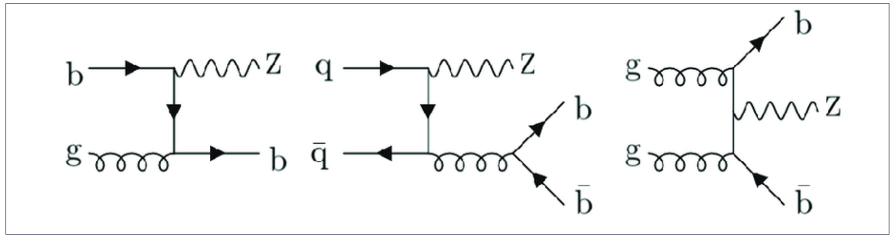
Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

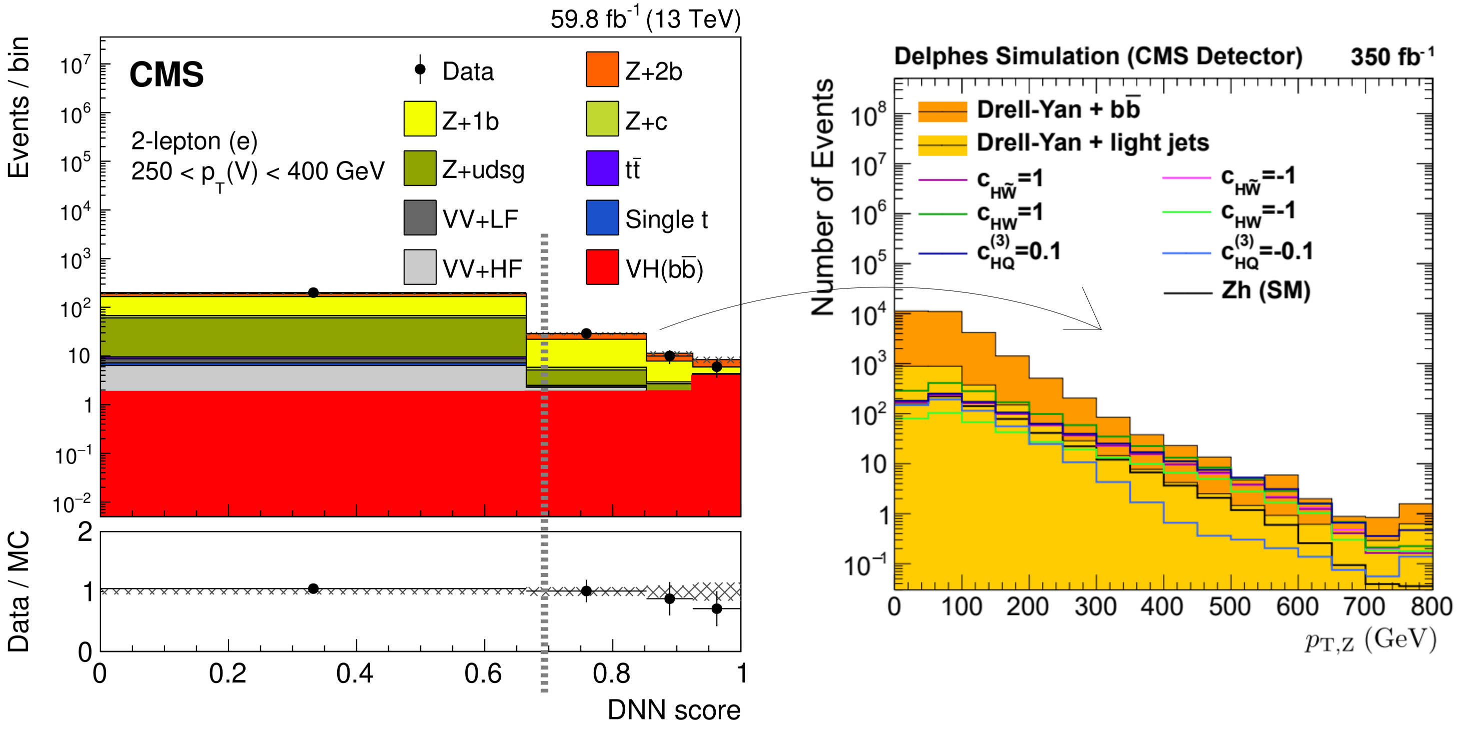
Signal



Background



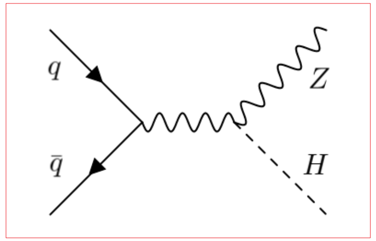
Traditional approach



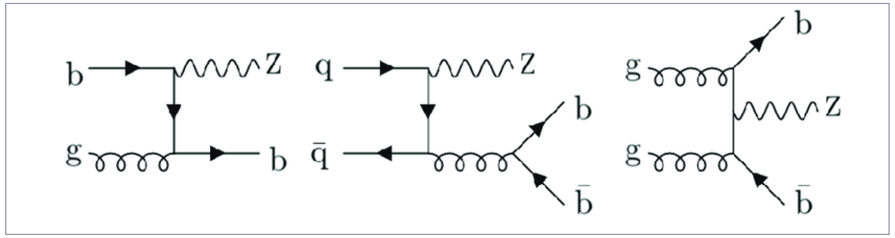
Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Signal



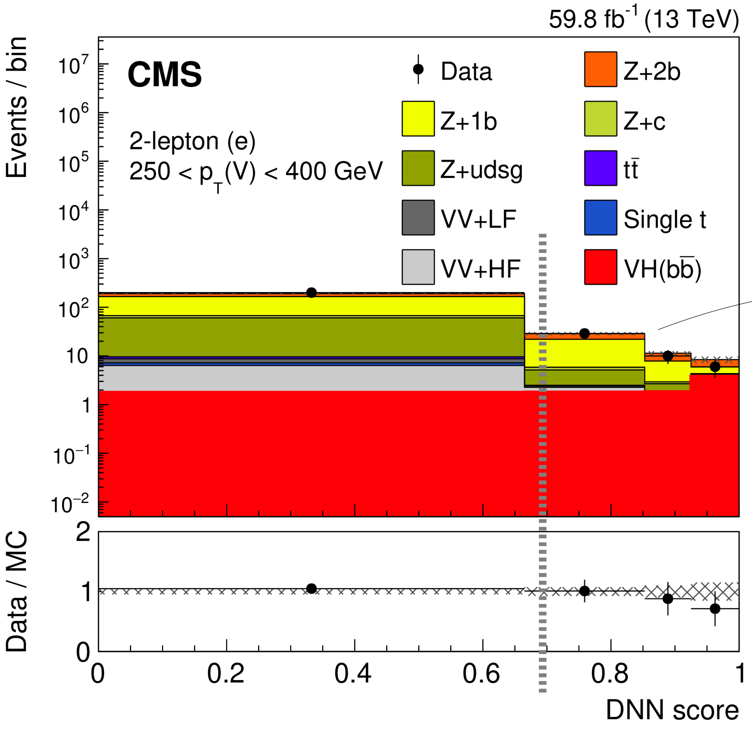
Background

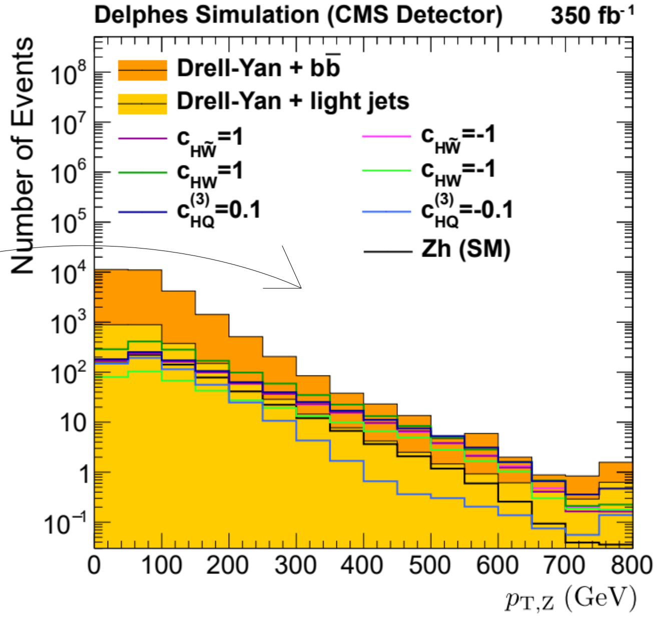


BIT approach

$$R(\boldsymbol{x}|\boldsymbol{\theta}_1, \boldsymbol{\theta}_0) = 1 + (\theta_1 - \theta_0)_a R_a(\boldsymbol{x}) + \frac{1}{2}(\theta_1 - \theta_0)_a(\theta_1 - \theta_0)_b R_{a,b}(\boldsymbol{x})$$

Traditional approach

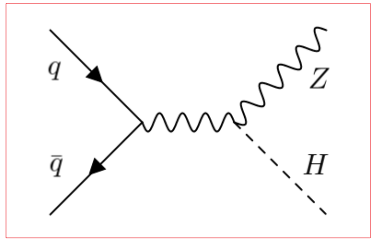




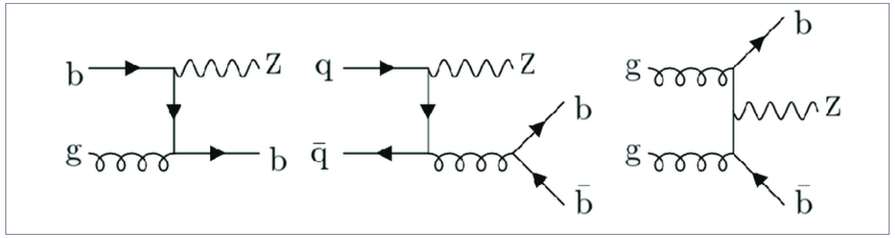
Learning SMEFT likelihood ratio

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Signal



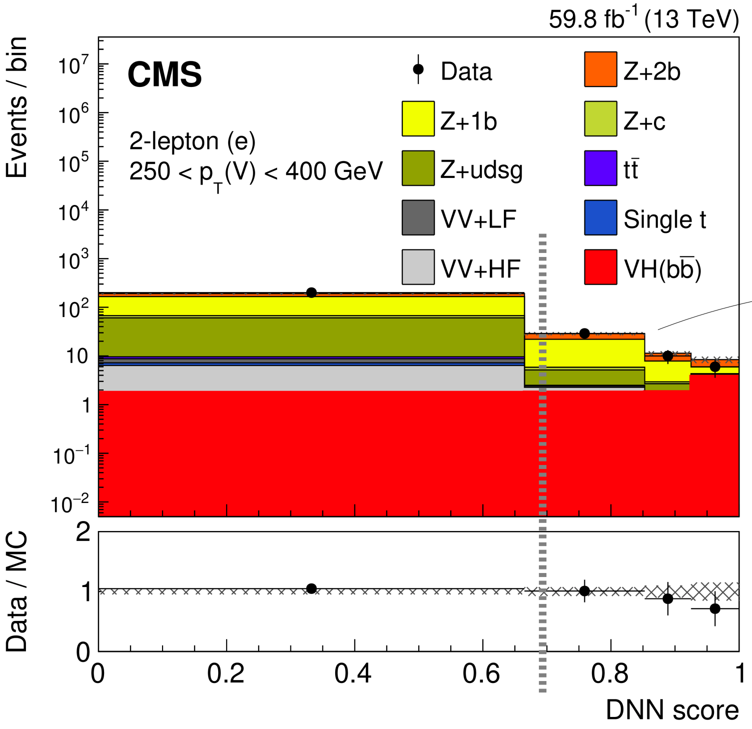
Background

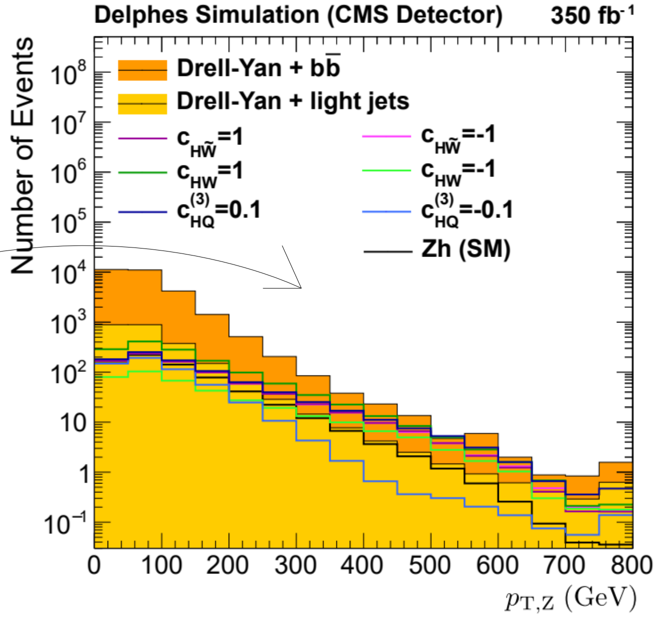


BIT approach

$$R(\boldsymbol{x}|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0) = 1 + (\theta_1-\theta_0)_a \boxed{R_a(\boldsymbol{x})} + \frac{1}{2}(\theta_1-\theta_0)_a(\theta_1-\theta_0)_b \boxed{R_{a,b}(\boldsymbol{x})}$$

Traditional approach

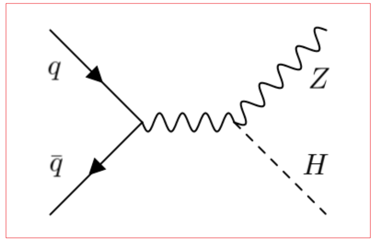




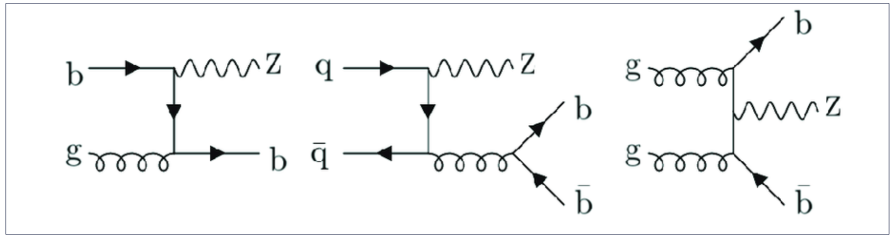
Learning SMEFT likelihood ratio

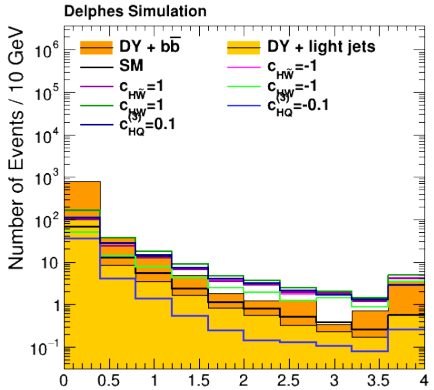
SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Signal



Background

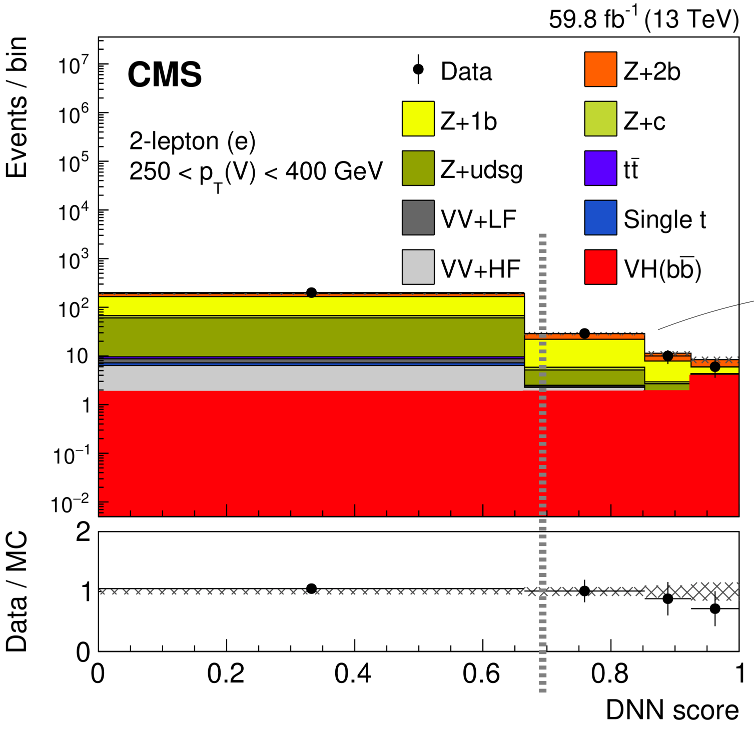


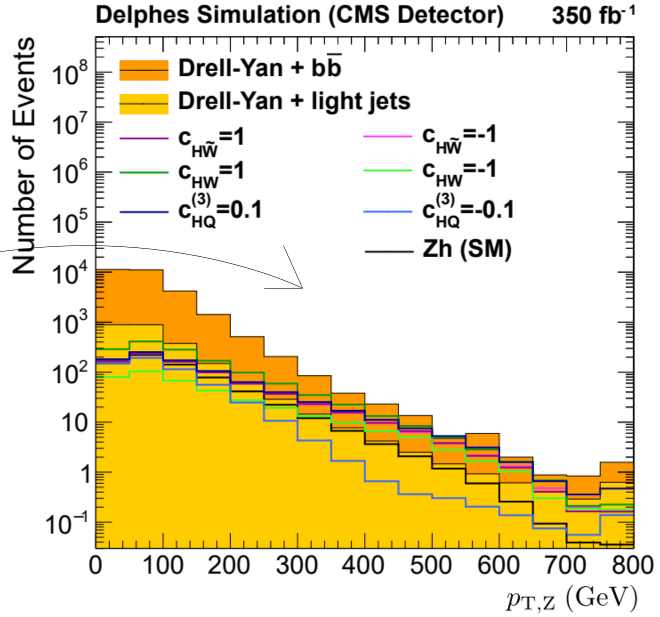


BIT approach

$$R(\boldsymbol{x}|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0) = 1 + (\theta_1-\theta_0)_a \boxed{R_a(\boldsymbol{x})} + \frac{1}{2}(\theta_1-\theta_0)_a(\theta_1-\theta_0)_b \boxed{R_{a,b}(\boldsymbol{x})}$$

Traditional approach

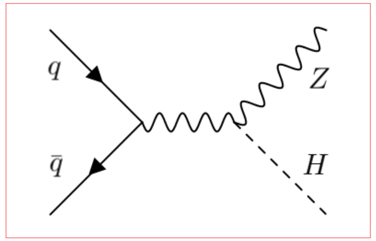




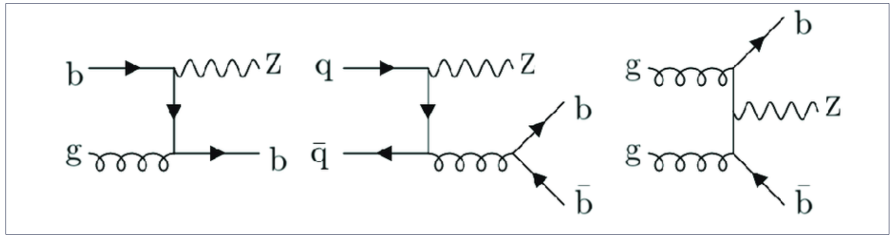
Learning SMEFT likelihood ratio

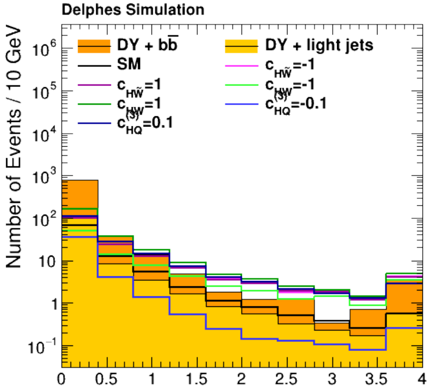
SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Signal



Background

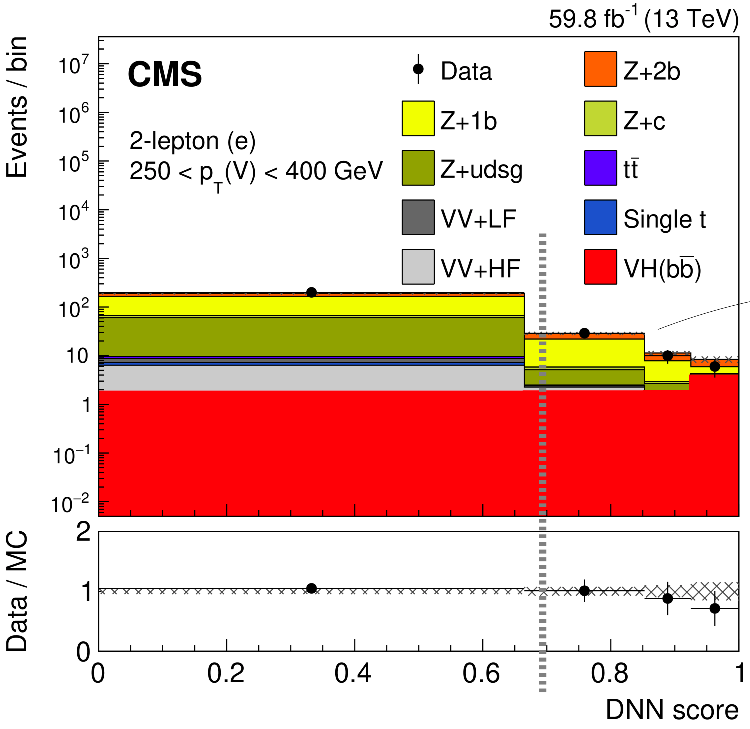


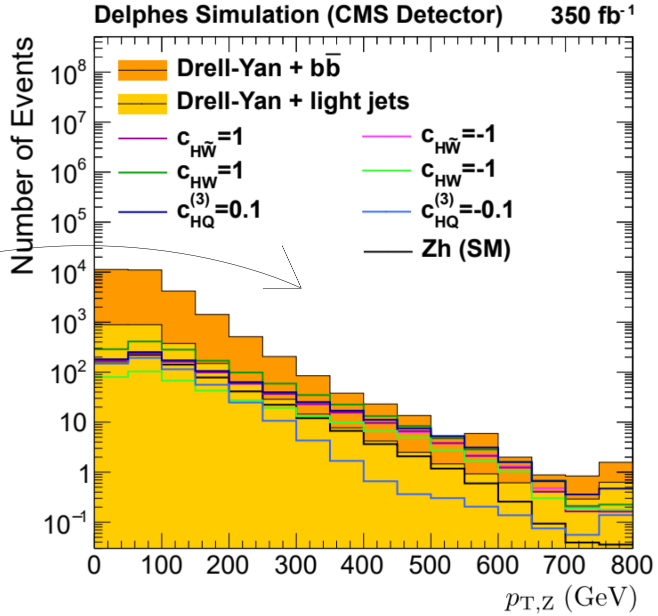


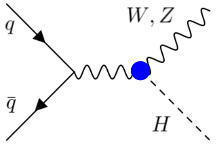
BIT approach

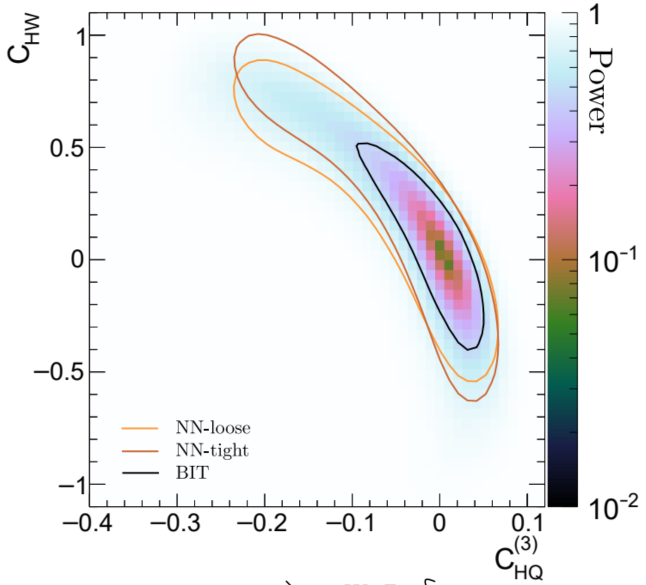
$$R(\boldsymbol{x}|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0) = 1 + (\theta_1-\theta_0)_a R_a(\boldsymbol{x}) + \frac{1}{2}(\theta_1-\theta_0)_a(\theta_1-\theta_0)_b R_{a,b}(\boldsymbol{x})$$

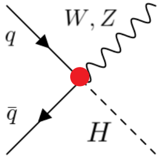
Traditional approach







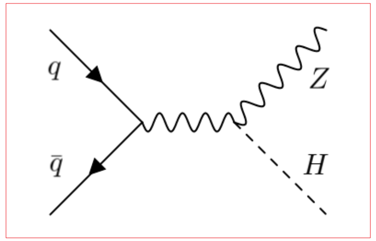




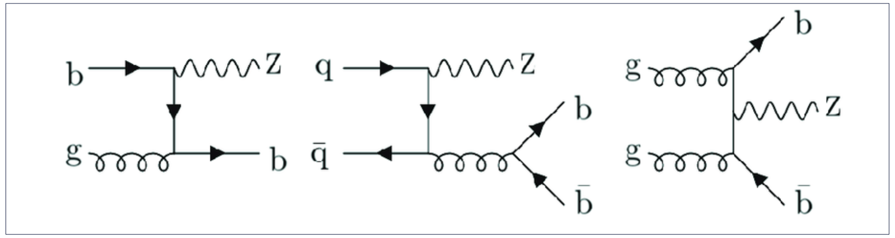
Learning SMEFT likelihood ratio

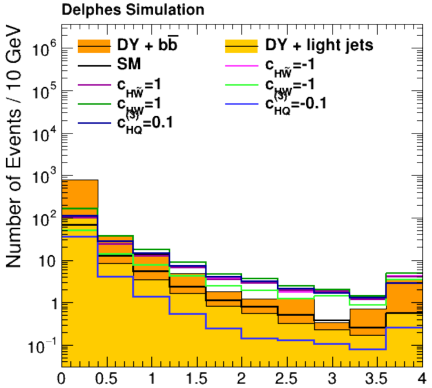
SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Signal



Background

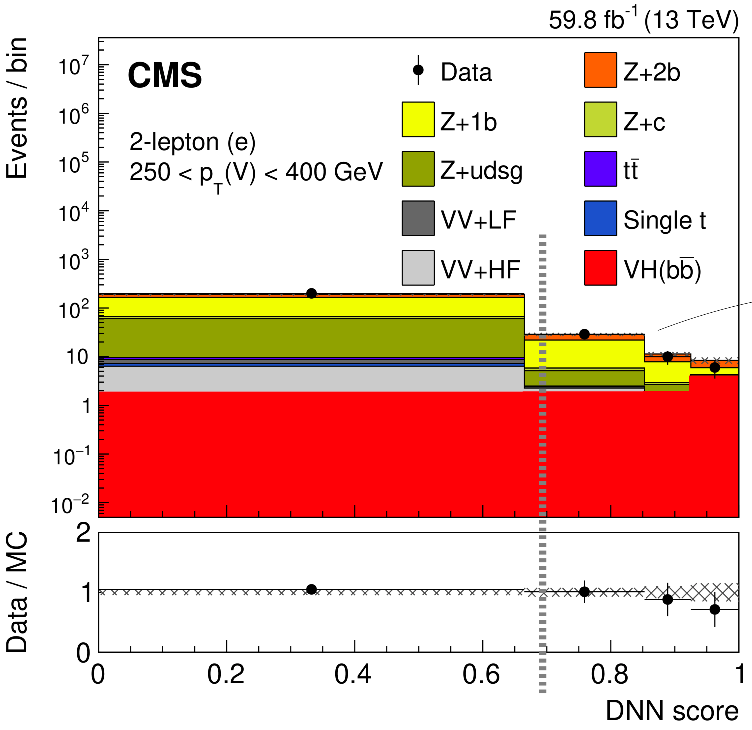


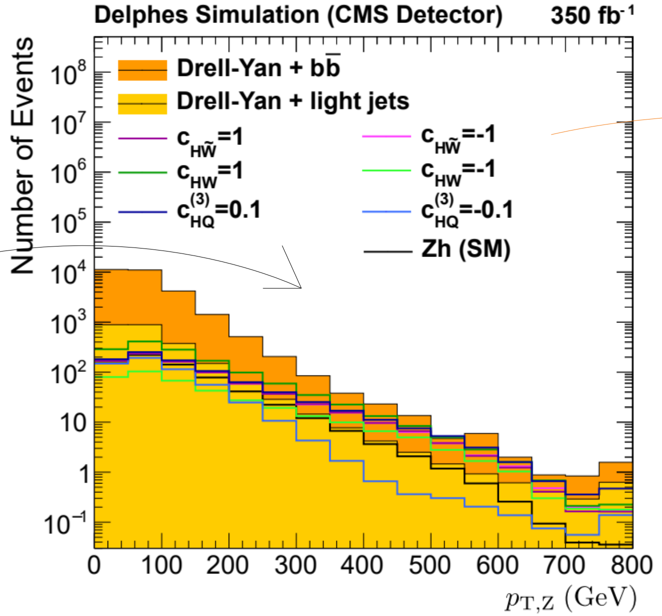


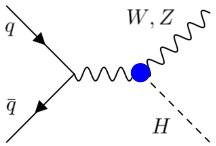
BIT approach

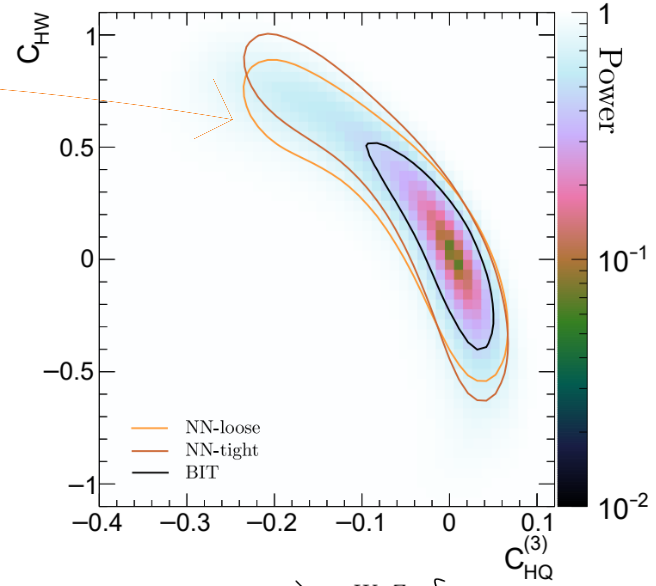
$$R(\boldsymbol{x}|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0) = 1 + (\theta_1-\theta_0)_a R_a(\boldsymbol{x}) + \frac{1}{2}(\theta_1-\theta_0)_a(\theta_1-\theta_0)_b R_{a,b}(\boldsymbol{x})$$

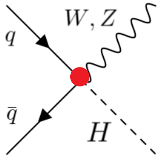
Traditional approach







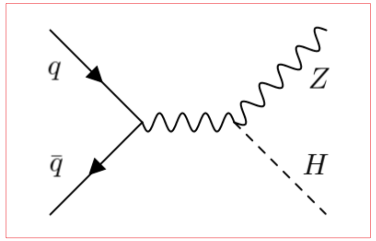




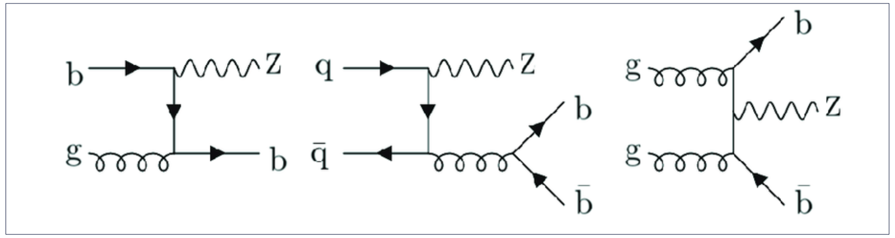
Learning SMEFT likelihood ratio

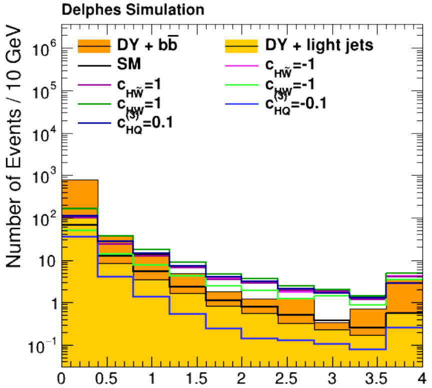
SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Signal



Background

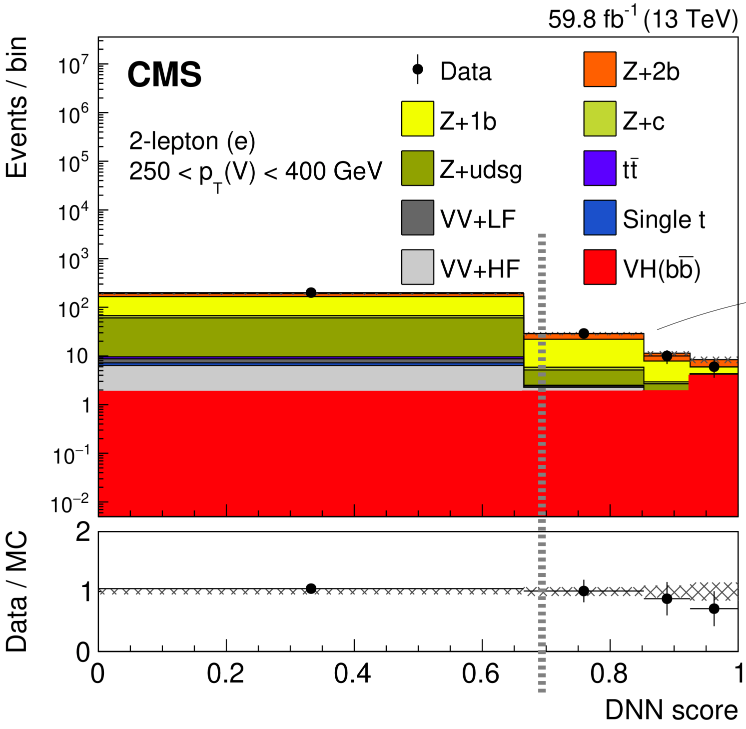


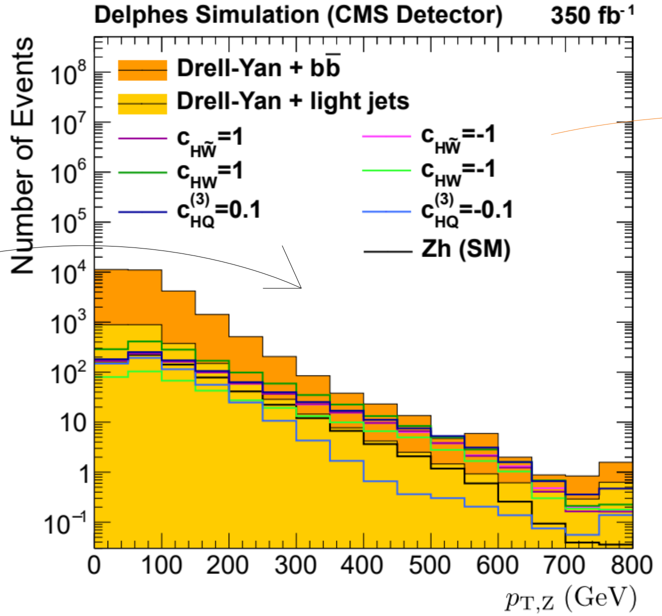


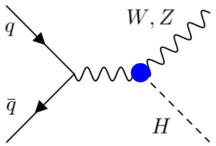
BIT approach

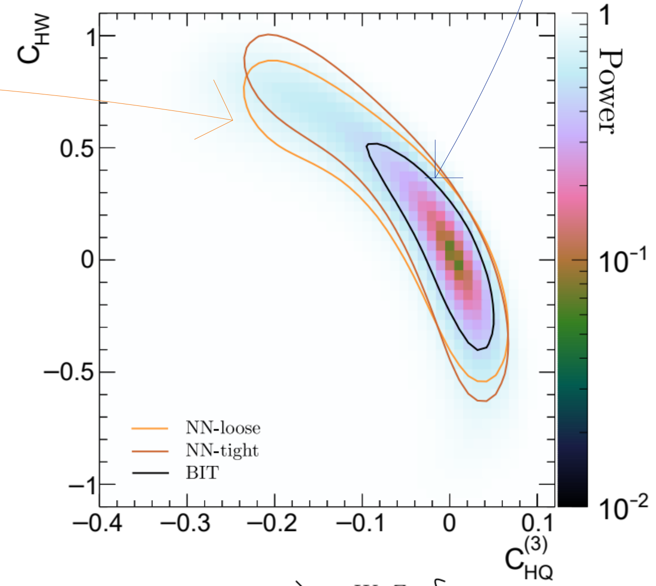
$$R(\boldsymbol{x}|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0) = 1 + (\theta_1-\theta_0)_a R_a(\boldsymbol{x}) + \frac{1}{2}(\theta_1-\theta_0)_a(\theta_1-\theta_0)_b R_{a,b}(\boldsymbol{x})$$

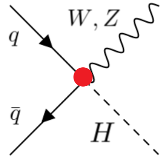
Traditional approach







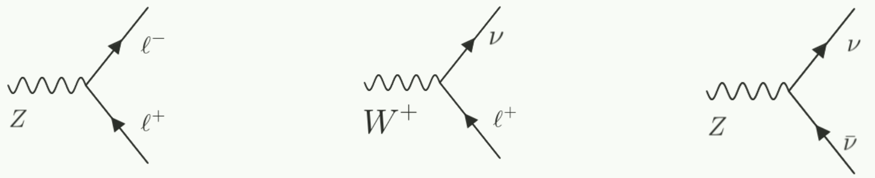




Event selection & categorization

Final state

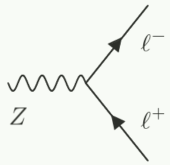
2-lepton 1-lepton 0-lepton



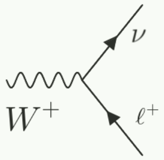
Event selection & categorization

Final state

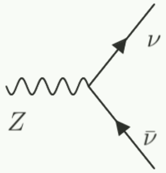
2-lepton



1-lepton



0-lepton

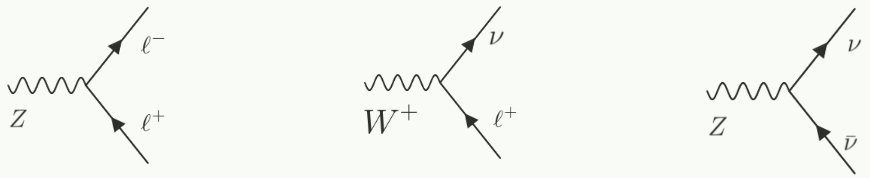


Regions

Event selection & categorization

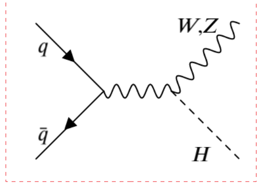
Final state

2-lepton 1-lepton 0-lepton



Regions

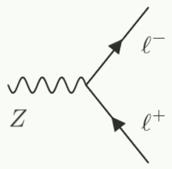
Signal region (SR)



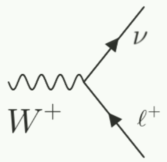
Event selection & categorization

Final state

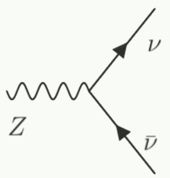
2-lepton



1-lepton

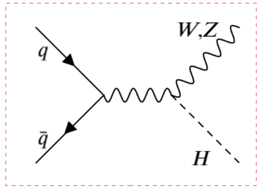


0-lepton



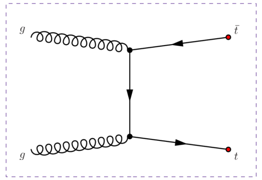
Regions

Signal region (SR)

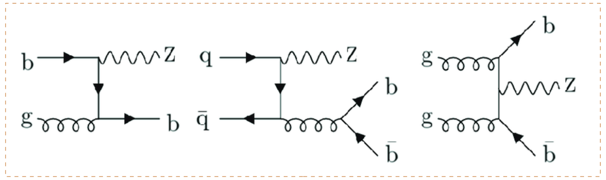


Control regions (CRs)

$t\bar{t}$



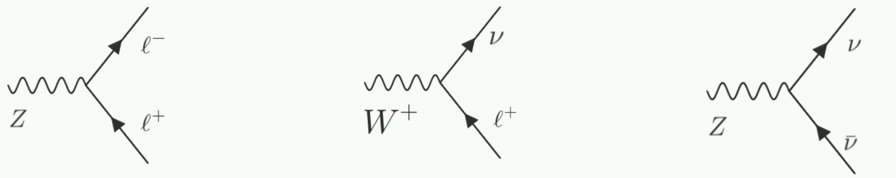
V+ heavy-flavor jets



Event selection & categorization

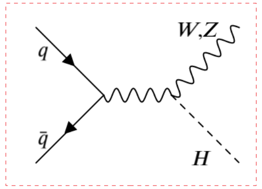
Final state

2-lepton 1-lepton 0-lepton



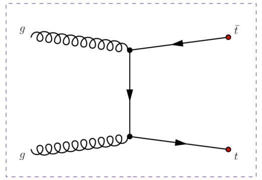
Regions

Signal region (SR)

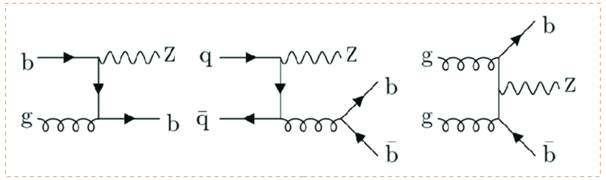


Control regions (CRs)

$t\bar{t}$



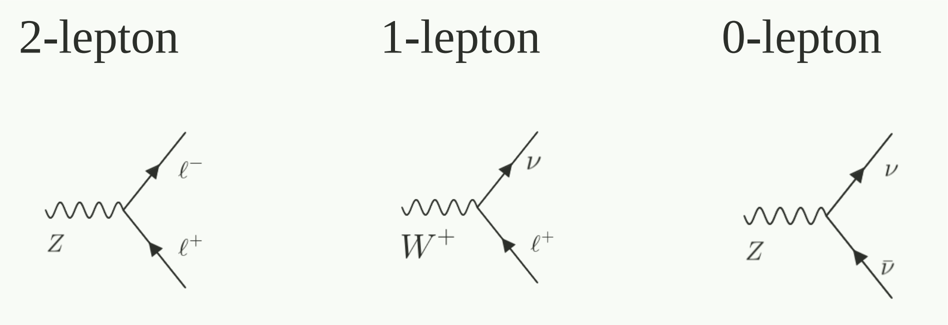
V+ heavy-flavor jets



Used to measure background

Event selection & categorization

Final state

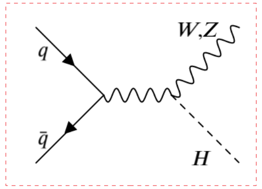

2-lepton

1-lepton

0-lepton

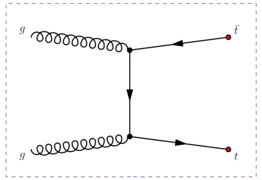
Regions

Signal region (SR)

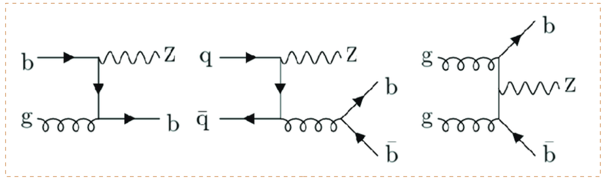


Control regions (CRs)

tt̄

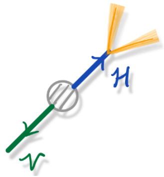


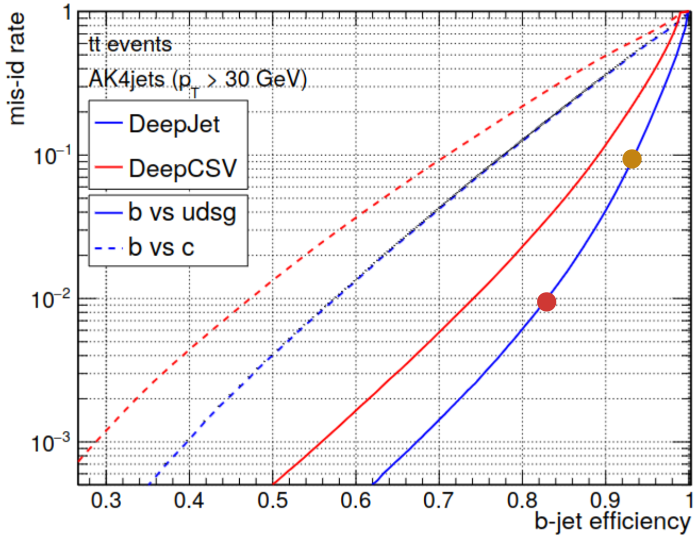
V+ heavy-flavor jets



Used to measure background

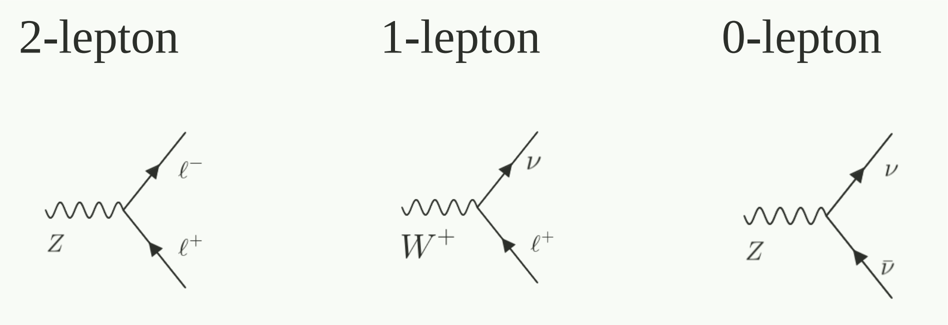
Bols, Kieseler, Verzetti, Stoye, Stakia (2020)





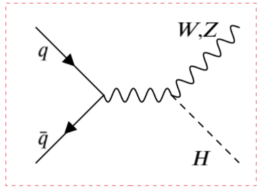
Event selection & categorization

Final state


2-lepton
1-lepton
0-lepton

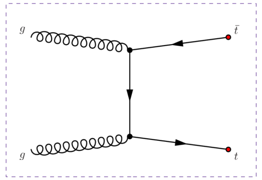
Regions

Signal region (SR)

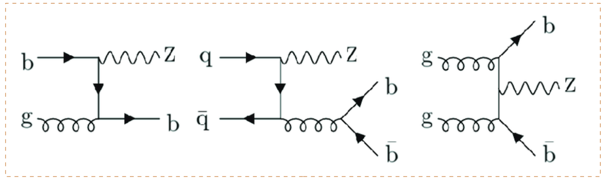


Control regions (CRs)

$t\bar{t}$

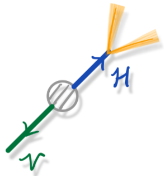


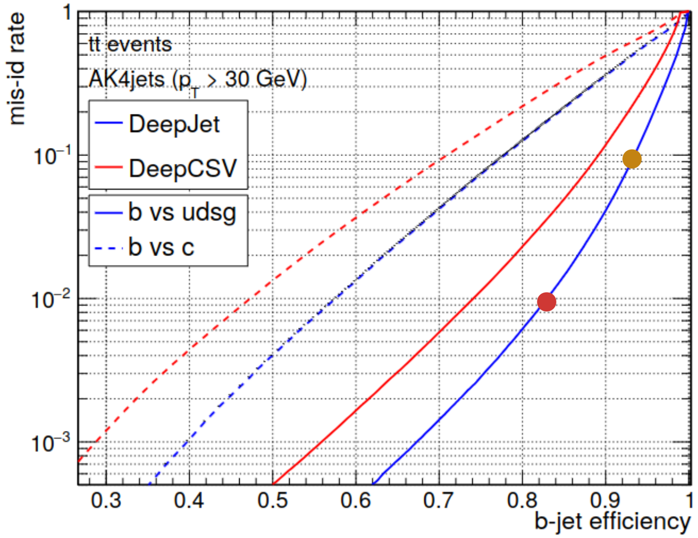
V+ heavy-flavor jets

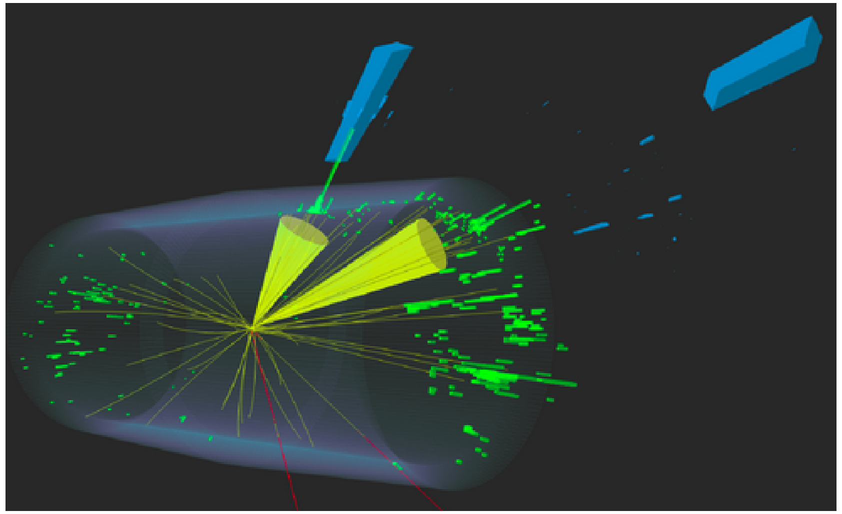


Used to measure background

Bols, Kieseler, Verzetti, Stoye, Stakia (2020)



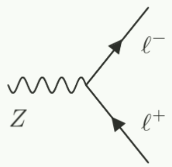




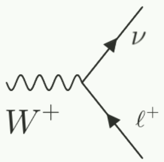
Event selection & categorization

Final state

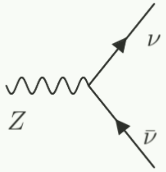
2-lepton



1-lepton

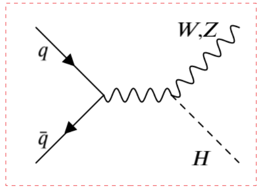


0-lepton



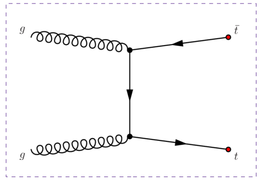
Regions

Signal region (SR)

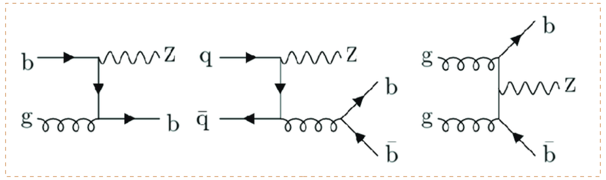


Control regions (CRs)

$t\bar{t}$

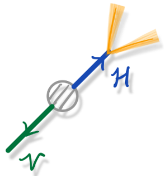


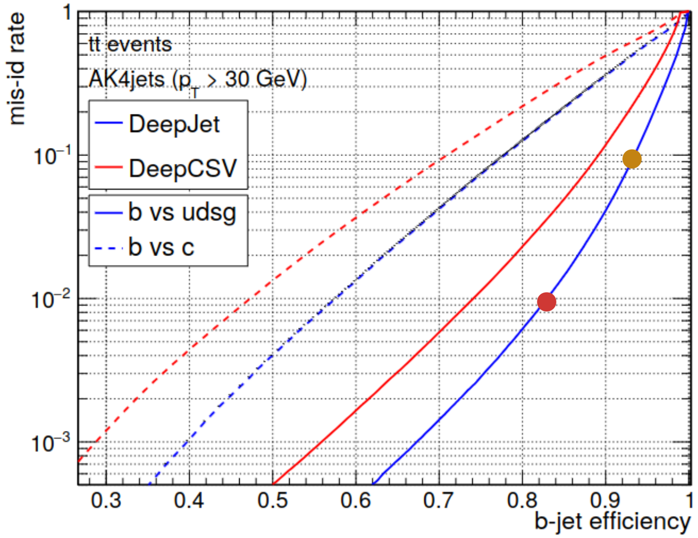
V+ heavy-flavor jets

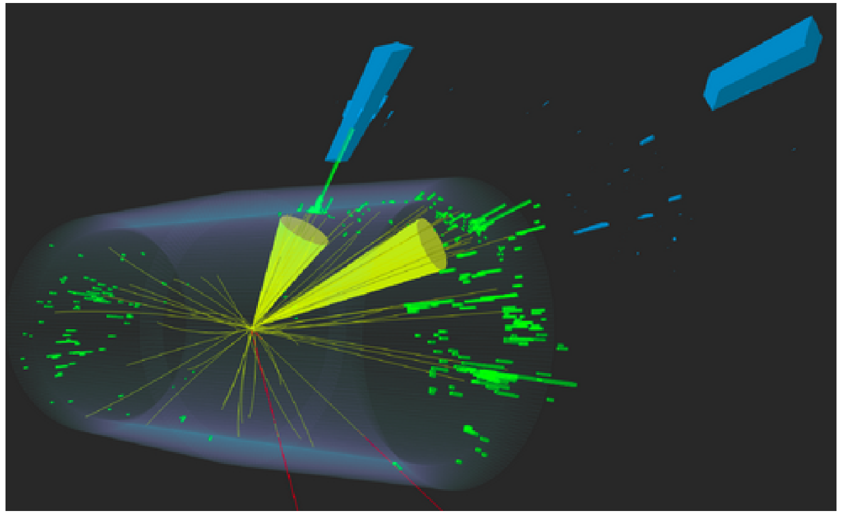


Used to measure background

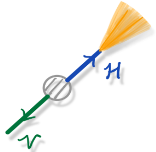
Bols, Kieseler, Verzetti, Stoye, Stakia (2020)

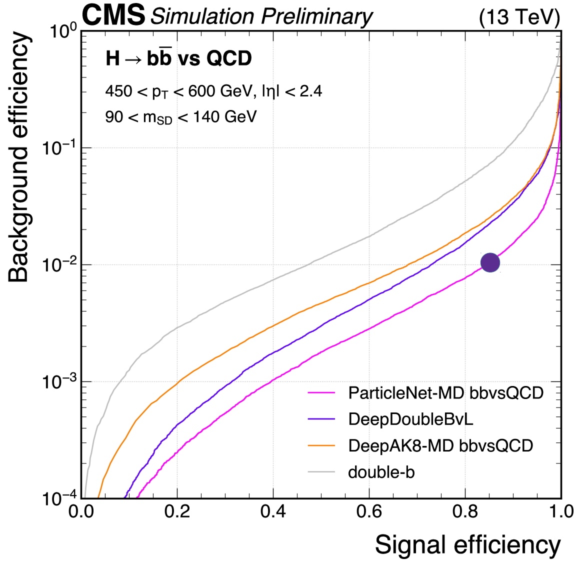






CMS-PAS-BTV-22-001





BIT training & template optimization

Objective:

SMEFT effects *vs*
- SM VH
- Background

BIT training & template optimization

`Objective:`

SMEFT effects *vs*
- SM VH
- Background

`Inputs:`

- Object kinematics
- Jet tagging scores
- Angular variables

BIT training & template optimization

arXiv: 2411.16907

`Objective:`

SMEFT effects *vs*
- SM VH
- Background

`Inputs:`

- Object kinematics
- Jet tagging scores
- Angular variables

`Template optimization`

Optimal performance guaranteed
if binning is chosen at each point in EFT space

very challenging

BIT training & template optimization

arXiv: 2411.16907

Objective:

SMEFT effects *vs*
- SM VH
- Background

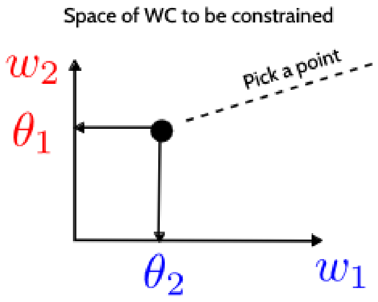
Inputs:

- Object kinematics
- Jet tagging scores
- Angular variables

Template optimization

Optimal performance guaranteed
if binning is chosen at each point in EFT space

very challenging



Template is chosen minimizing ∏ 2σ intervals (profiled)

← Find the point in EFT space

BIT training & template optimization

arXiv: 2411.16907

Objective:

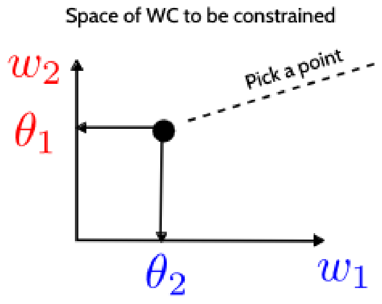
SMEFT effects *vs*
- SM VH
- Background

No EFT effects considered in background

Inputs:

- Object kinematics
- Jet tagging scores
- Angular variables

Template optimization



Optimal performance guaranteed
if binning is chosen at each point in EFT space

very challenging

Template is chosen minimizing $\prod$ 2σ intervals (profiled)

← Find the point in EFT space

BIT training & template optimization

arXiv: 2411.16907

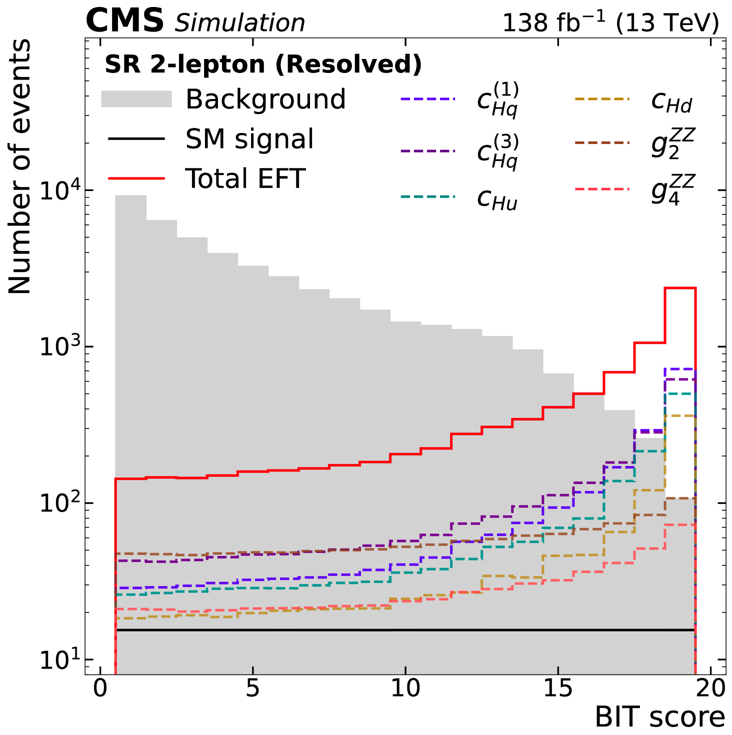
Objective:

SMEFT effects *vs*
- SM VH
- Background

Inputs:

- Object kinematics
- Jet tagging scores
- Angular variables

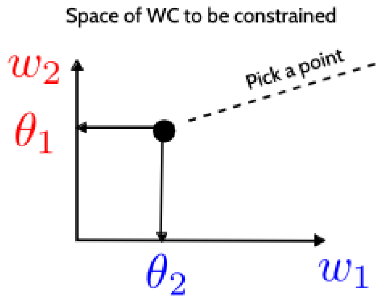
No EFT effects considered in background



Template optimization

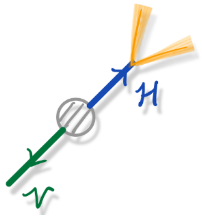
Optimal performance guaranteed
if binning is chosen at each point in EFT space

very challenging



Template is chosen minimizing $\prod$ 2σ intervals (profiled)

← Find the point in EFT space



BIT training & template optimization

arXiv: 2411.16907

Objective:

SMEFT effects *vs*
- SM VH
- Background

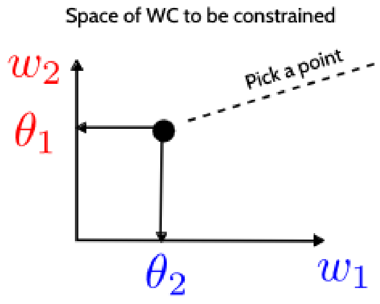
Inputs:

- Object kinematics
- Jet tagging scores
- Angular variables

Template optimization

Optimal performance guaranteed
if binning is chosen at each point in EFT space

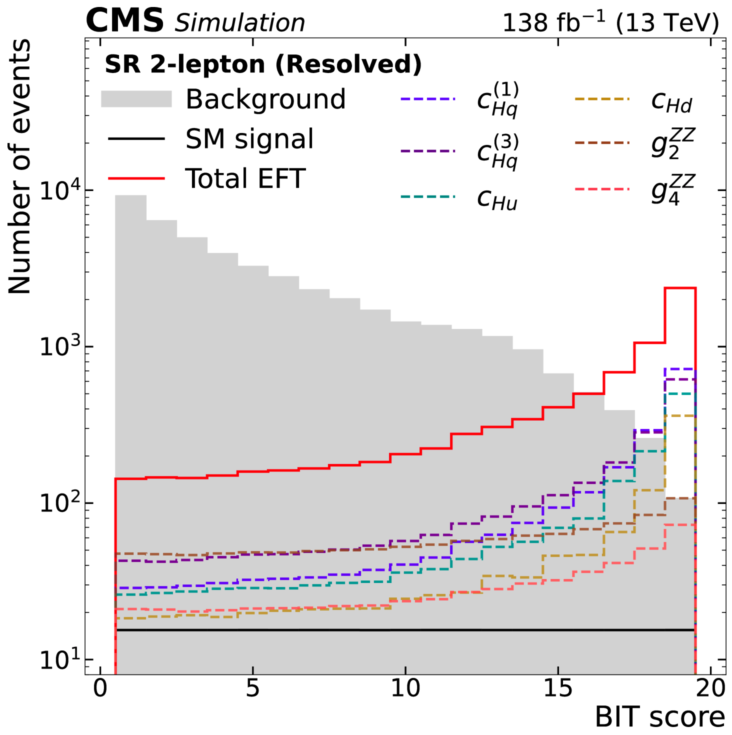
very challenging

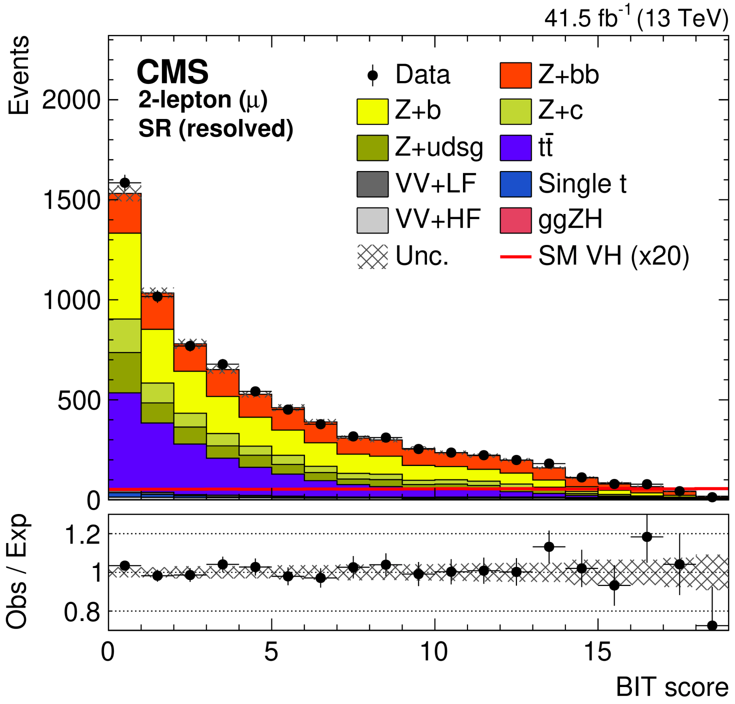


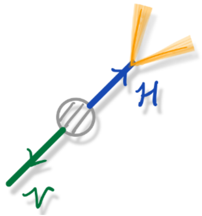
No EFT effects considered in background

Template is chosen minimizing ∏ 2σ intervals (profiled)

← Find the point in EFT space







BIT training & template optimization

arXiv: 2411.16907

Objective:

SMEFT effects *vs*
- SM VH
- Background

Inputs:

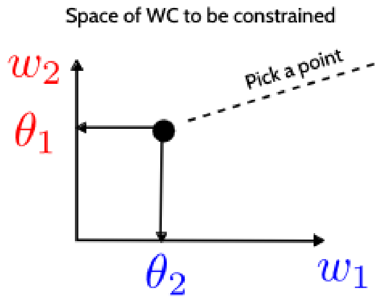
- Object kinematics
- Jet tagging scores
- Angular variables

No EFT effects considered in background

Template optimization

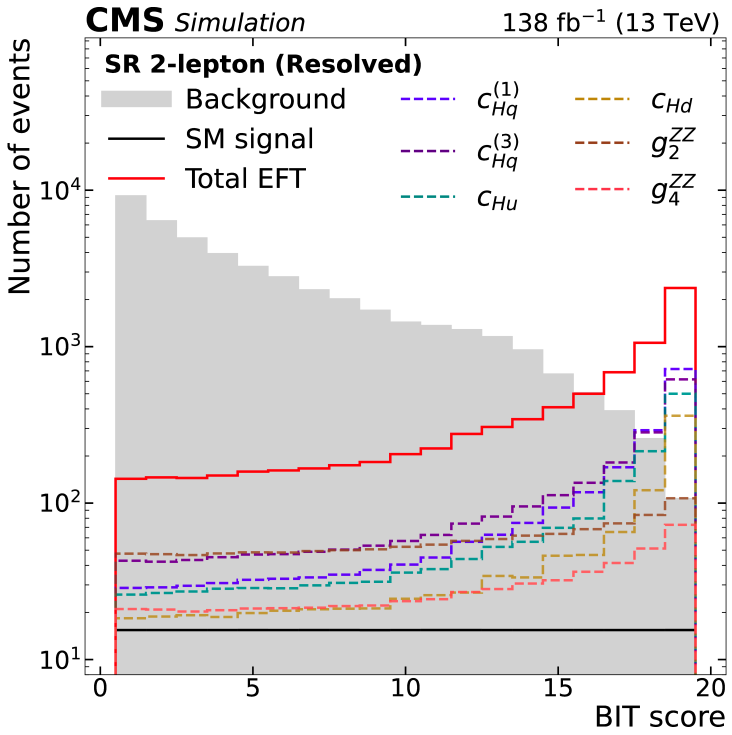
Optimal performance guaranteed
if binning is chosen at each point in EFT space

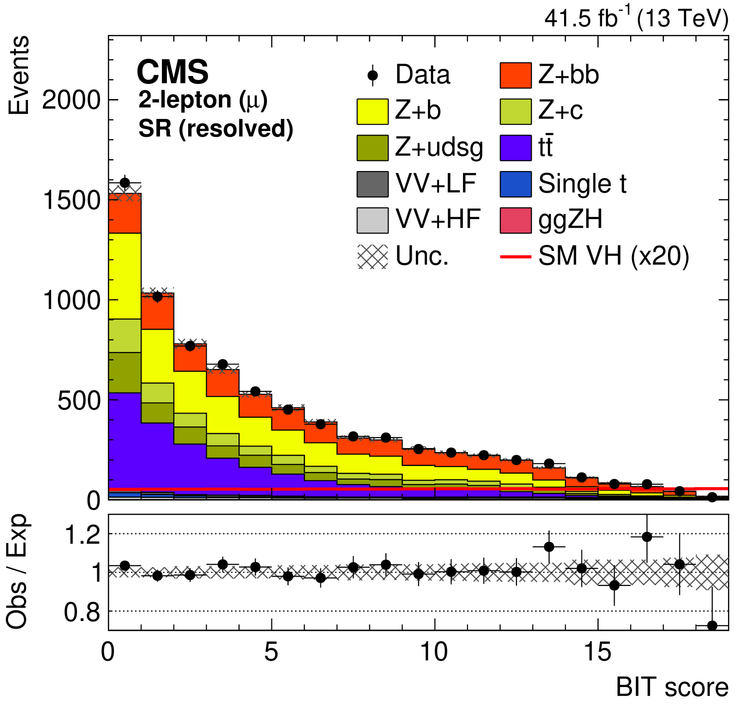
very challenging

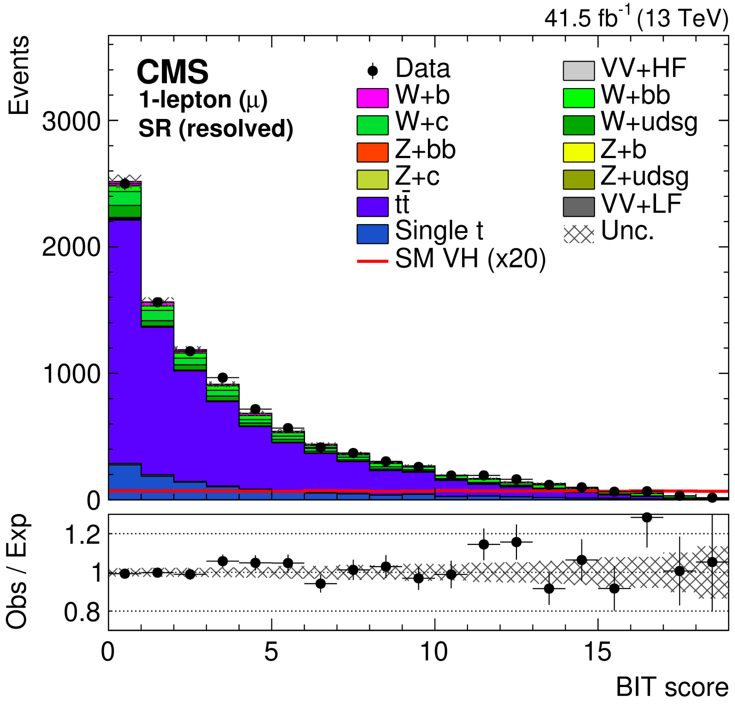


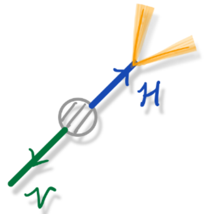
Template is chosen minimizing $\prod$ 2σ intervals (profiled)

← Find the point in EFT space









BIT training & template optimization

arXiv: 2411.16907

Objective:

SMEFT effects *vs*
- SM VH
- Background

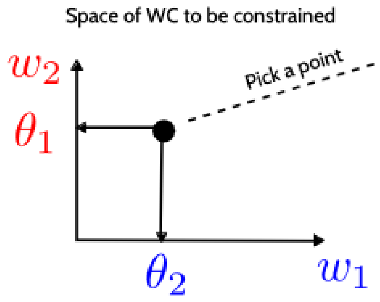
Inputs:

- Object kinematics
- Jet tagging scores
- Angular variables

Template optimization

Optimal performance guaranteed
if binning is chosen at each point in EFT space

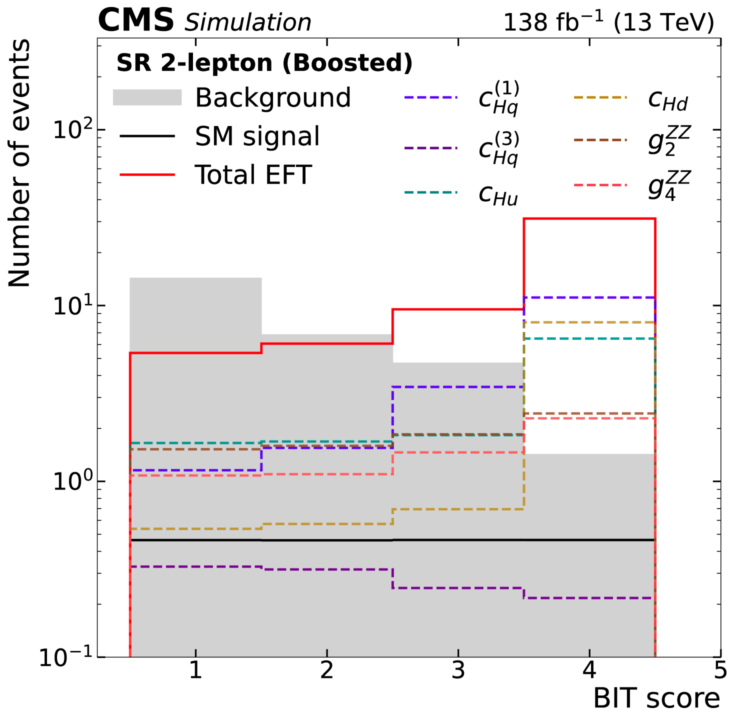
very challenging

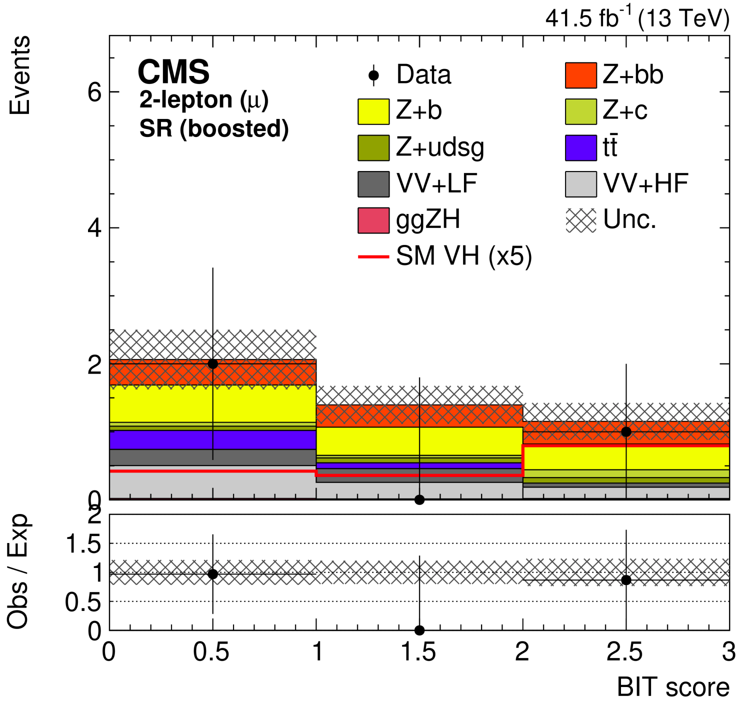


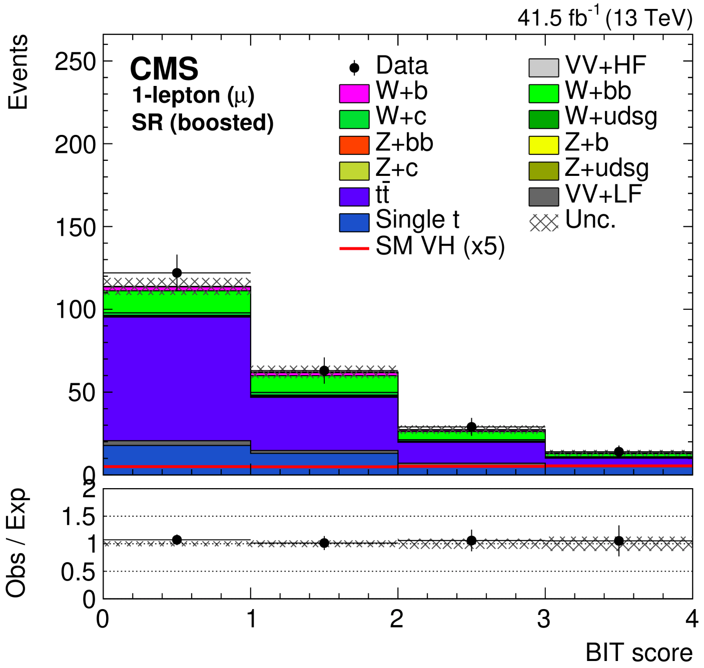
No EFT effects considered in background

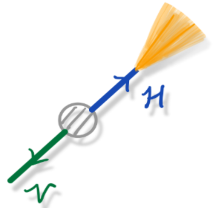
Template is chosen minimizing $\prod$ 2σ intervals (profiled)

← Find the point in EFT space









EFT interpretation: Wilson coefficients

With linear or
full quadratic
expansion

$$\sigma \sim |\mathcal{M}_{\mathrm{SMEFT}}|^2$$

$$\sim |\mathcal{M}_{\mathrm{SM}}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}^{\dagger}_{\mathrm{SM}} \mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{c_i^2}{\Lambda^4} |\mathcal{M}_{6,\mathrm{i}}|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4} \mathcal{M}_{6,\mathrm{i}} \mathcal{M}_{6,\mathrm{j}}$$

Λ = 1 TeV

EFT interpretation: Wilson coefficients

With linear or
full quadratic
expansion

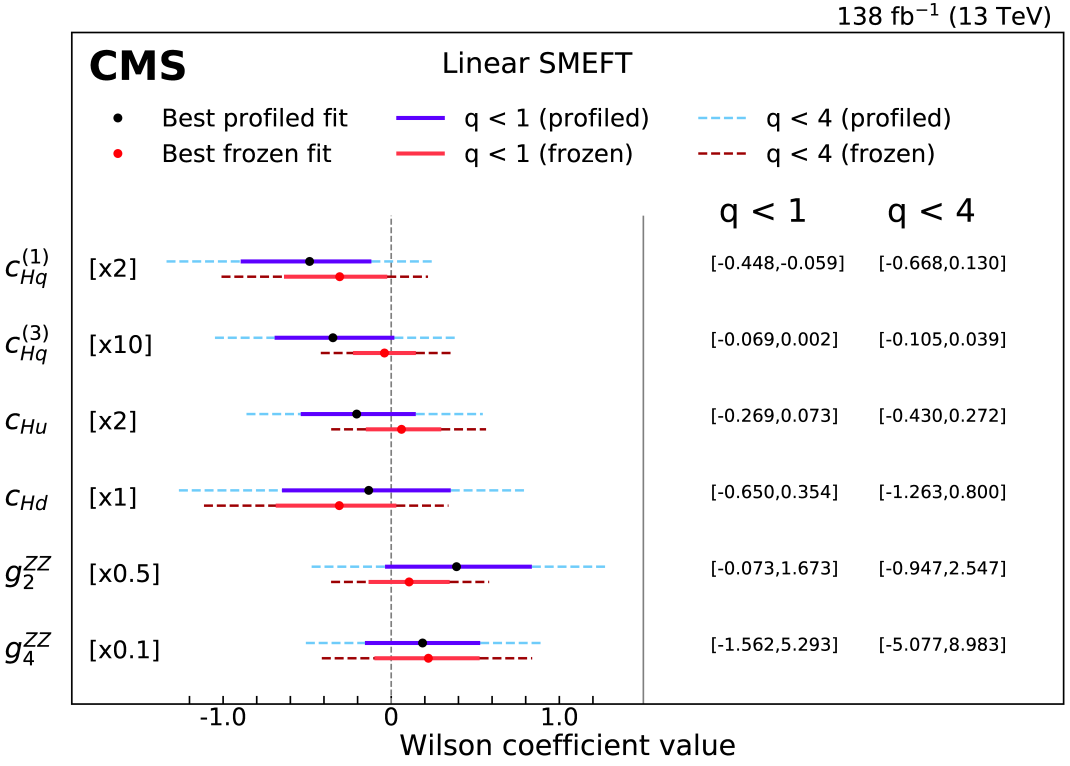
$$\sigma \sim |\mathcal{M}_{\mathrm{SMEFT}}|^2$$

$$\sim \boxed{|\mathcal{M}_{\mathrm{SM}}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}_{\mathrm{SM}}^\dagger \mathcal{M}_{6,i})} + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,i}|^2 + \sum_i\sum_{j,j>i}\frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,i}\mathcal{M}_{6,j}$$

Λ = 1 TeV

Compatibility with SM while varying
all coefficients together

p-value = 73%



EFT interpretation: Wilson coefficients

With linear or
full quadratic
expansion

$$\sigma \sim \left|\mathcal{M}_{\mathrm{SMEFT}}\right|^2$$

$$\sim \left|\mathcal{M}_{\mathrm{SM}}\right|^2 + \sum_i \frac{c_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}_{\mathrm{SM}}^{\dagger}\mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{c_i^2}{\Lambda^4}\left|\mathcal{M}_{6,\mathrm{i}}\right|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,\mathrm{i}}\mathcal{M}_{6,\mathrm{j}}$$

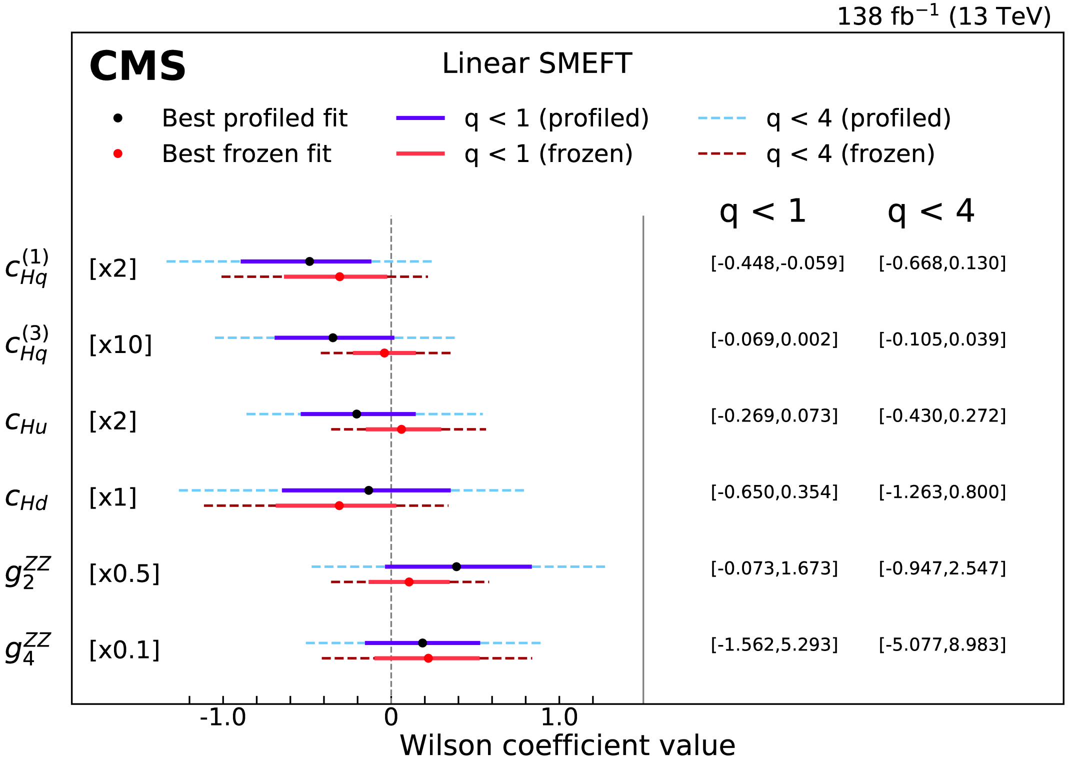
Λ = 1 TeV

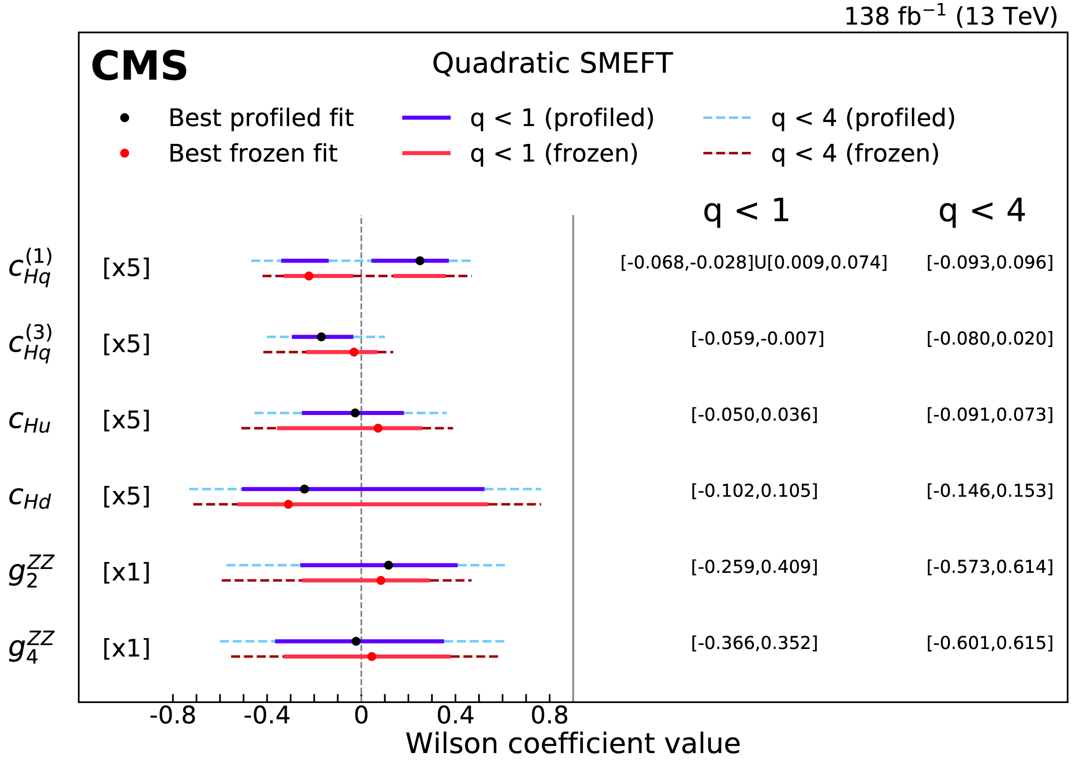
Compatibility with SM while varying
all coefficients together

arXiv: 2411.16907

p-value = 73%

p-value = 84%





EFT interpretation: Wilson coefficients

With linear or
full quadratic
expansion

$$\sigma \sim |\mathcal{M}_{\text{SMEFT}}|^2$$

$$\sim |\mathcal{M}_{\text{SM}}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2\text{Re}(\mathcal{M}_{\text{SM}}^\dagger \mathcal{M}_{6,\text{i}}) + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,\text{i}}|^2 + \sum_i\sum_{j,j>i}\frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,\text{i}}\mathcal{M}_{6,\text{j}}$$

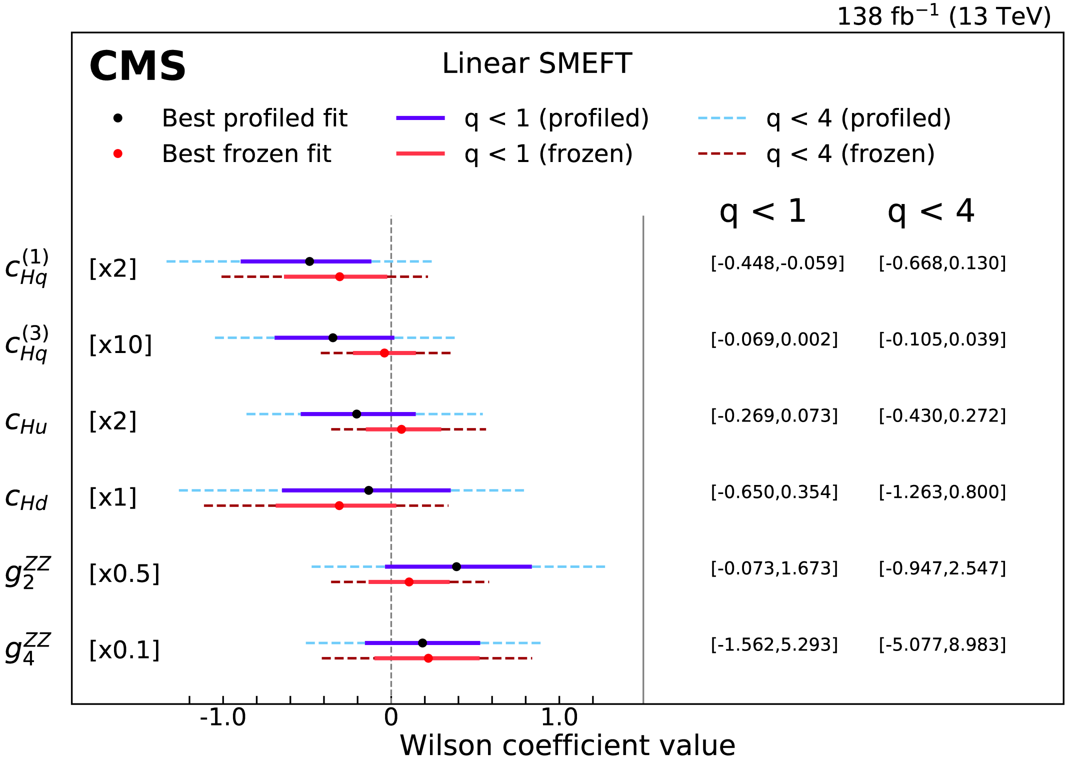
Λ = 1 TeV

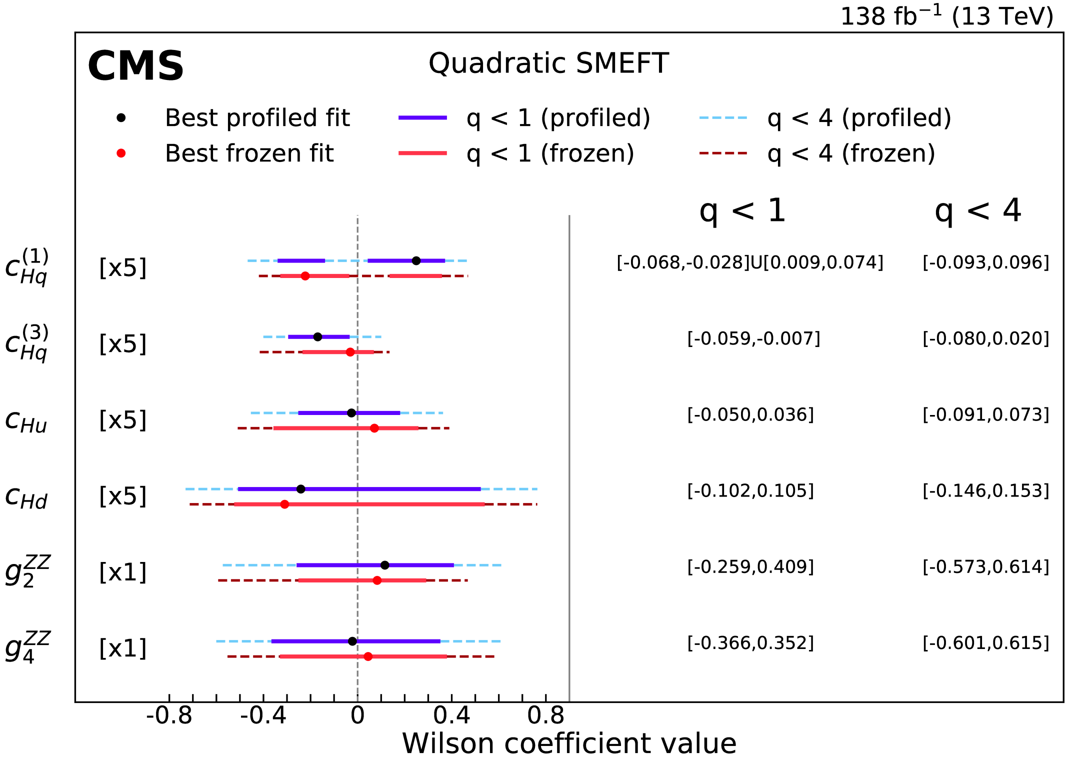
Compatibility with SM while varying
all coefficients together

arXiv: 2411.16907

p-value = 73%

p-value = 84%





Quadratic component dominates sensitivity for most coefficients

EFT interpretation: energy scale

With linear or full quadratic expansion

$$\sigma \sim |\mathcal{M}_{\rm SMEFT}|^2$$

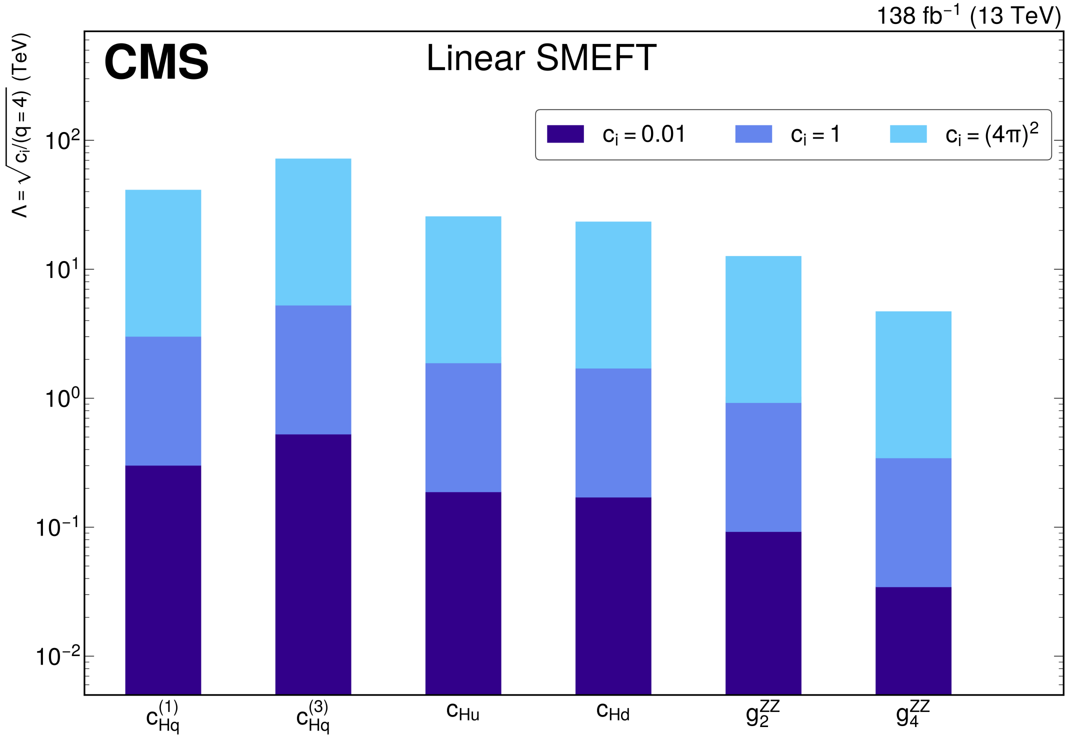
$$\sim \boxed{|\mathcal{M}_{\rm SM}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2{\rm Re}(\mathcal{M}_{\rm SM}^{\dagger}\mathcal{M}_{6,i})} + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,i}|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,i}\mathcal{M}_{6,j}$$

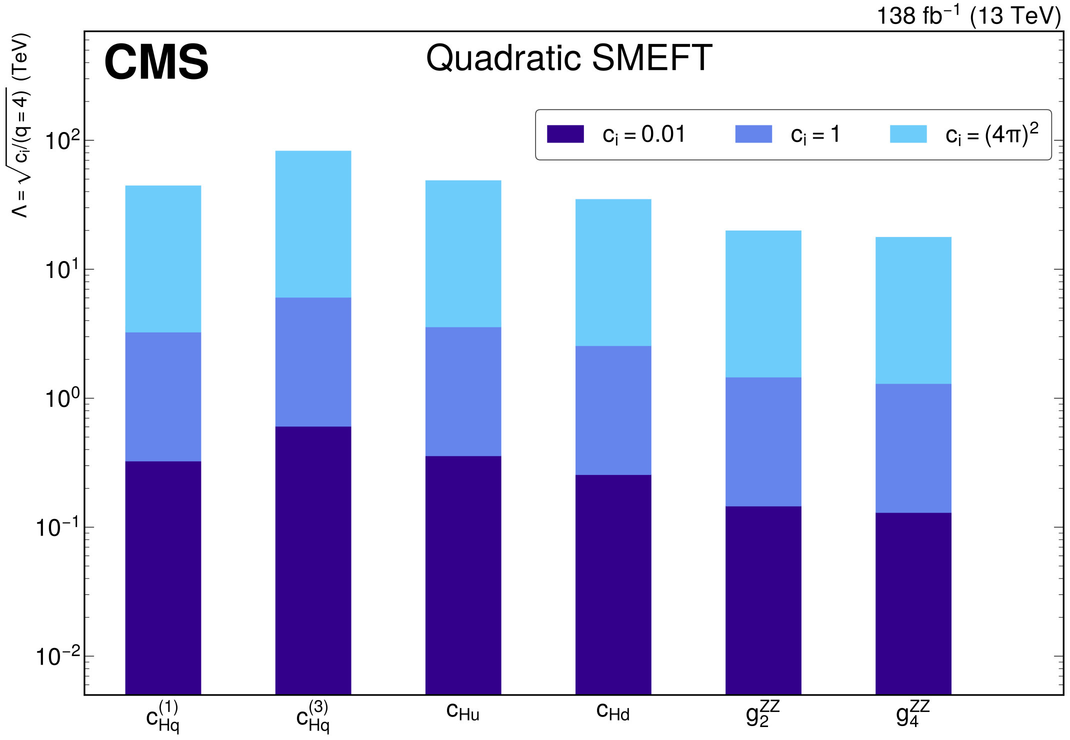
Lower bound on Λ

Three BSM scenarios:

- weakly coupled model (c=0.01)
- no assumption (c=1)
- strongly-coupling perturbativity limit ($c=16\pi^2$)

arXiv: 2411.16907





Sensitivity: ~ few TeV for c=1

EFT interpretation: Wilson coefficients in 2D

With
full quadratic
expansion

$$\sigma \sim |\mathcal{M}_{\rm SMEFT}|^2$$
$$\boxed{\sim |\mathcal{M}_{\rm SM}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2{\rm Re}(\mathcal{M}^{\dagger}_{\rm SM}\mathcal{M}_{6,i}) + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,i}|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,i}\mathcal{M}_{6,j}}$$

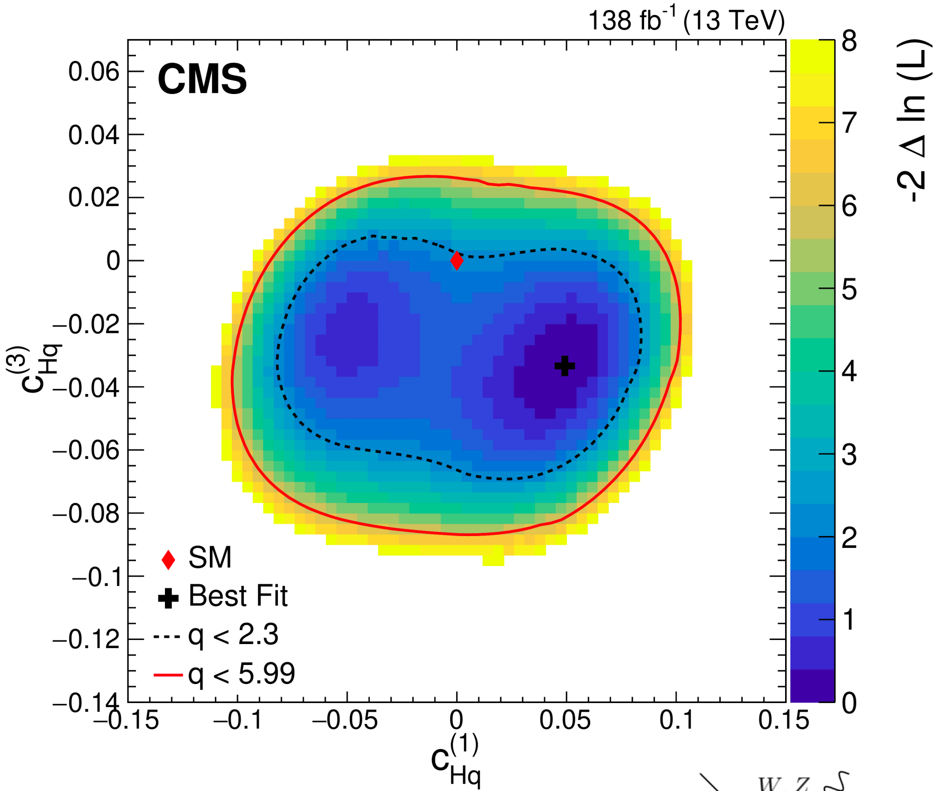
$\Lambda = 1$ TeV

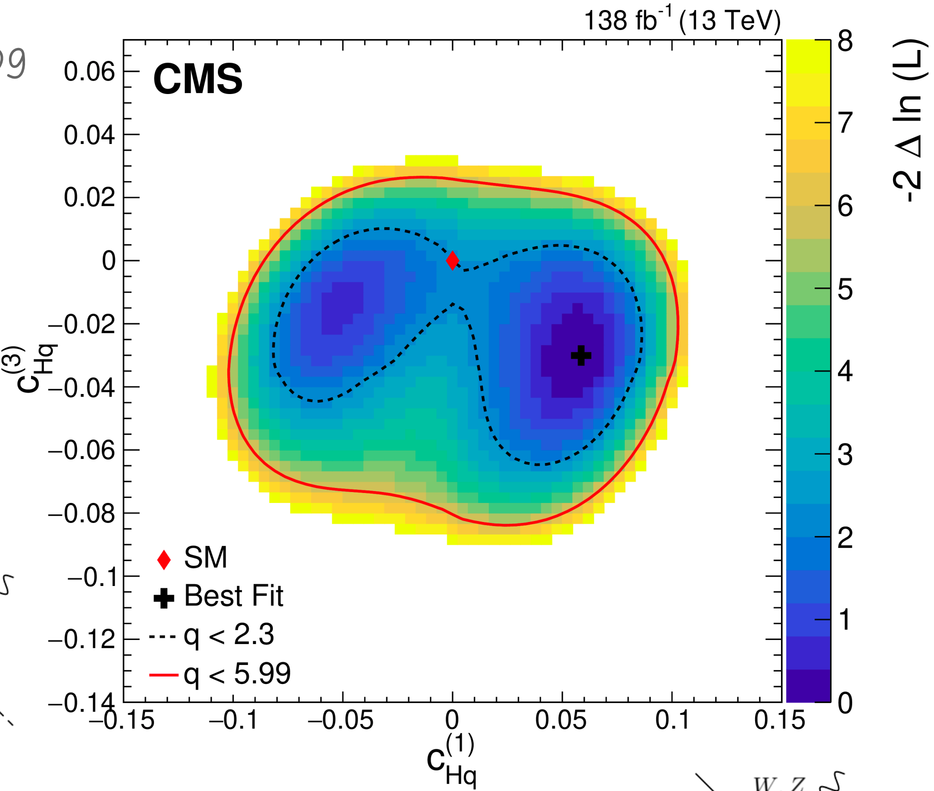
Other coefficients profiled

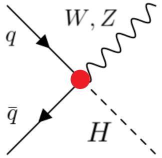
Vector coupling
vs.
Vector coupling

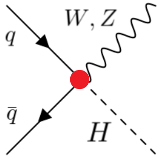
Other coefficients fixed at 0

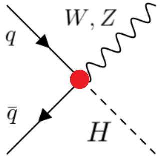
arXiv: 2411.16907

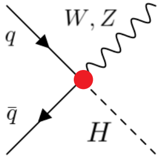












EFT interpretation: Wilson coefficients in 2D

With
full quadratic
expansion

$$\sigma \sim |\mathcal{M}_{\mathrm{SMEFT}}|^2$$

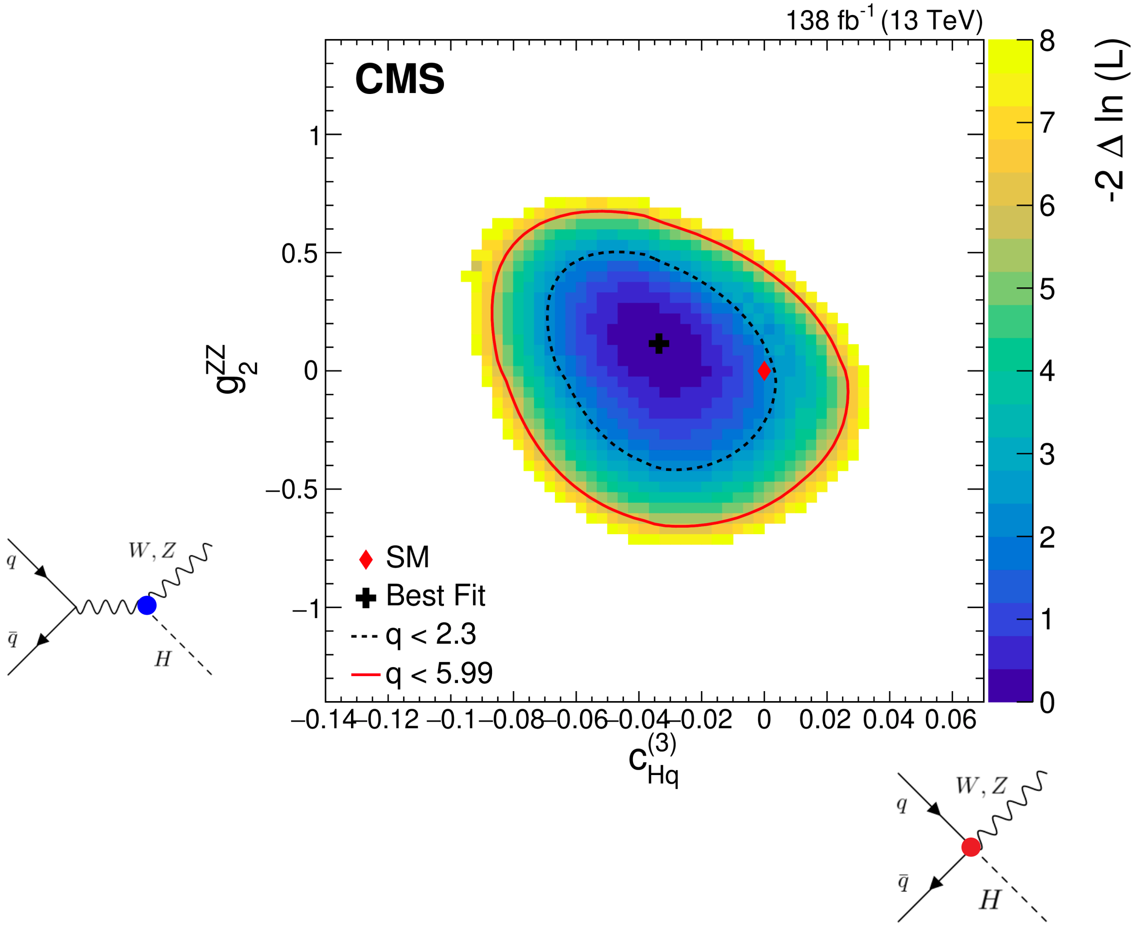
$$\boxed{\sim |\mathcal{M}_{\mathrm{SM}}|^2 + \sum_i \frac{c_i}{\Lambda^2} 2\mathrm{Re}(\mathcal{M}_{\mathrm{SM}}^{\dagger}\mathcal{M}_{6,\mathrm{i}}) + \sum_i \frac{c_i^2}{\Lambda^4}|\mathcal{M}_{6,\mathrm{i}}|^2 + \sum_i \sum_{j,j>i} \frac{c_i c_j}{\Lambda^4}\mathcal{M}_{6,\mathrm{i}}\mathcal{M}_{6,\mathrm{j}}}$$

$\Lambda = 1$ TeV

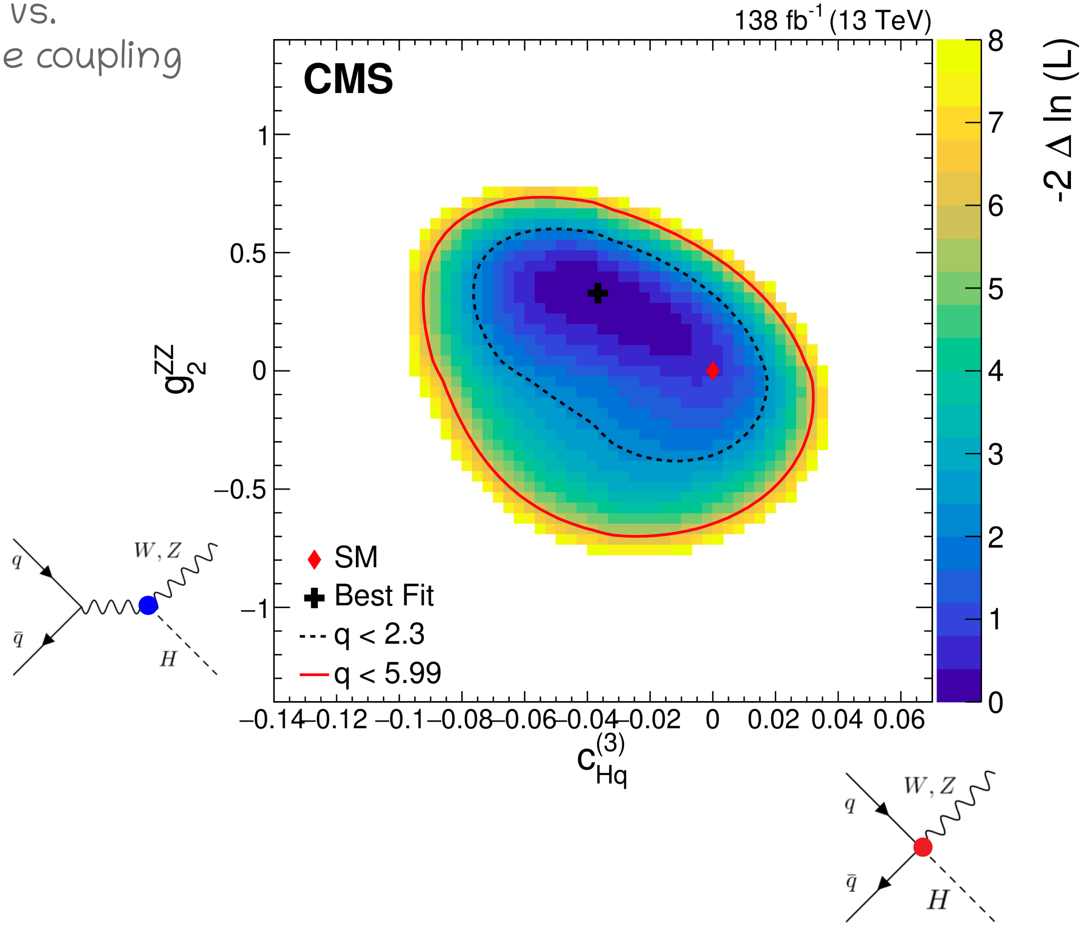
arXiv: 2411.16907

Vector coupling
vs.
Gauge coupling

Other coefficients profiled

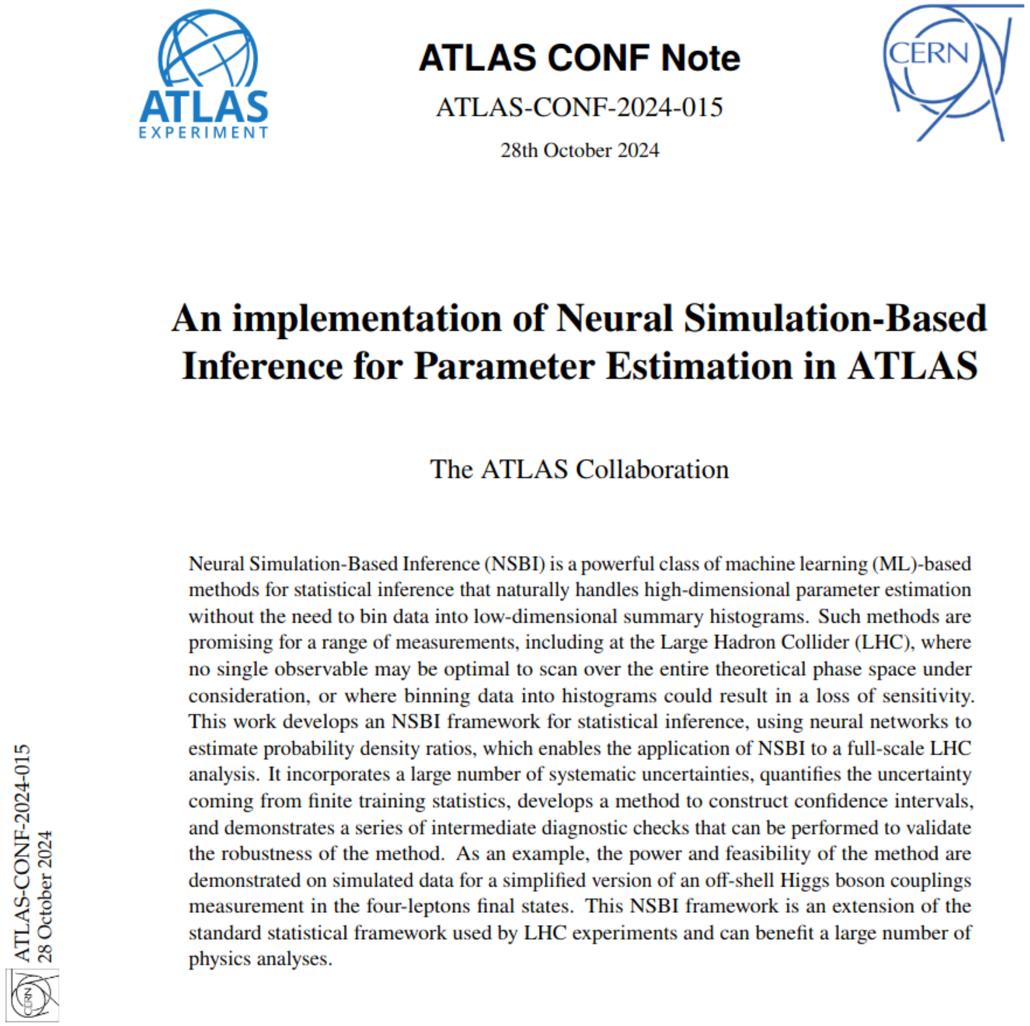


Other coefficients fixed at 0



Highlights

In K. Cranmer's DESY Colloquium



ATLAS CONF Note

ATLAS-CONF-2024-015

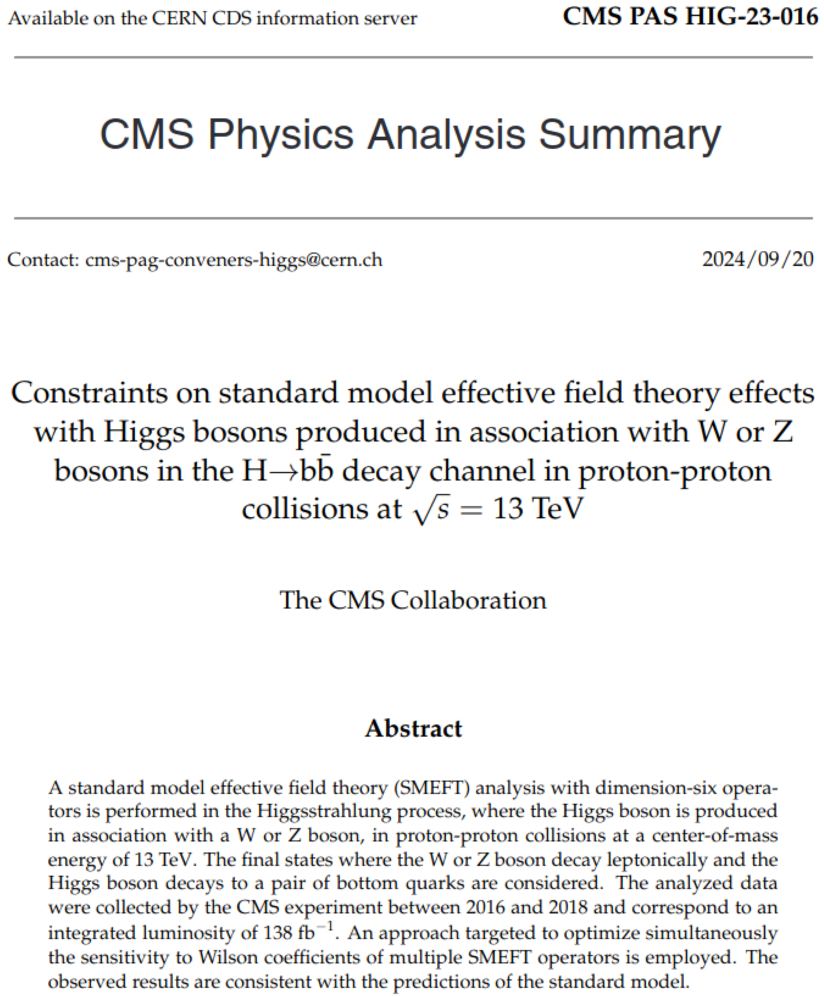
28th October 2024

An implementation of Neural Simulation-Based Inference for Parameter Estimation in ATLAS

The ATLAS Collaboration

Neural Simulation-Based Inference (NSBI) is a powerful class of machine learning (ML)-based methods for statistical inference that naturally handles high-dimensional parameter estimation without the need to bin data into low-dimensional summary histograms. Such methods are promising for a range of measurements, including at the Large Hadron Collider (LHC), where no single observable may be optimal to scan over the entire theoretical phase space under consideration, or where binning data into histograms could result in a loss of sensitivity. This work develops an NSBI framework for statistical inference, using neural networks to estimate probability density ratios, which enables the application of NSBI to a full-scale LHC analysis. It incorporates a large number of systematic uncertainties, quantifies the uncertainty coming from finite training statistics, develops a method to construct confidence intervals, and demonstrates a series of intermediate diagnostic checks that can be performed to validate the robustness of the method. As an example, the power and feasibility of the method are demonstrated on simulated data for a simplified version of an off-shell Higgs boson couplings measurement in the four-leptons final states. This NSBI framework is an extension of the standard statistical framework used by LHC experiments and can benefit a large number of physics analyses.

ATLAS-CONF-2024-015
28 October 2024



Available on the CERN CDS information server **CMS PAS HIG-23-016**

CMS Physics Analysis Summary

Contact: cms-pag-conveners-higgs@cern.ch 2024/09/20

Constraints on standard model effective field theory effects with Higgs bosons produced in association with W or Z bosons in the $H \to b\bar{b}$ decay channel in proton-proton collisions at $\sqrt{s} = 13$ TeV

The CMS Collaboration

Abstract

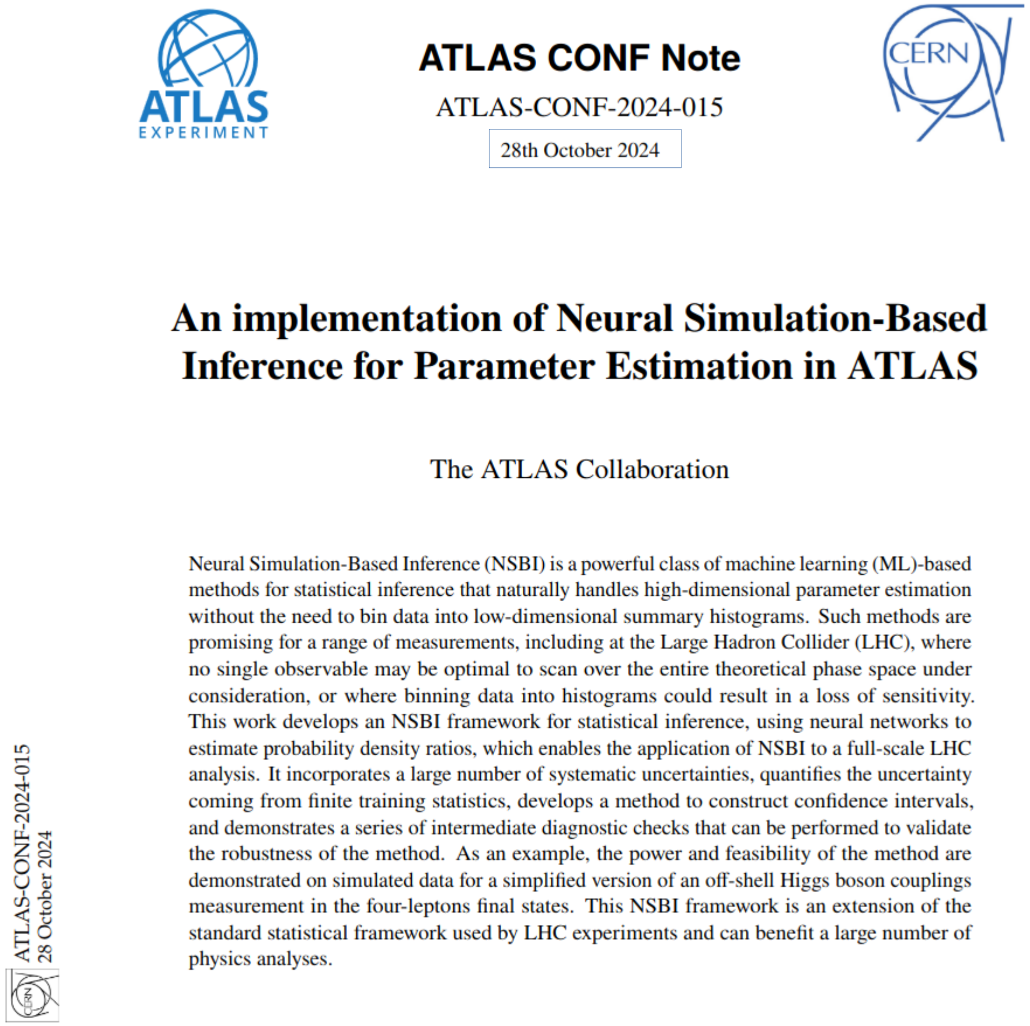
A standard model effective field theory (SMEFT) analysis with dimension-six operators is performed in the Higgsstrahlung process, where the Higgs boson is produced in association with a W or Z boson, in proton-proton collisions at a center-of-mass energy of 13 TeV. The final states where the W or Z boson decay leptonically and the Higgs boson decays to a pair of bottom quarks are considered. The analyzed data were collected by the CMS experiment between 2016 and 2018 and correspond to an integrated luminosity of 138 fb^{-1}. An approach targeted to optimize simultaneously the sensitivity to Wilson coefficients of multiple SMEFT operators is employed. The observed results are consistent with the predictions of the standard model.

ATLAS used simulation-based inference for off-shell H production

Neural network-based approach: arXiv: 2412.01548

Highlights

In K. Cranmer's DESY Colloquium



ATLAS CONF Note

ATLAS-CONF-2024-015

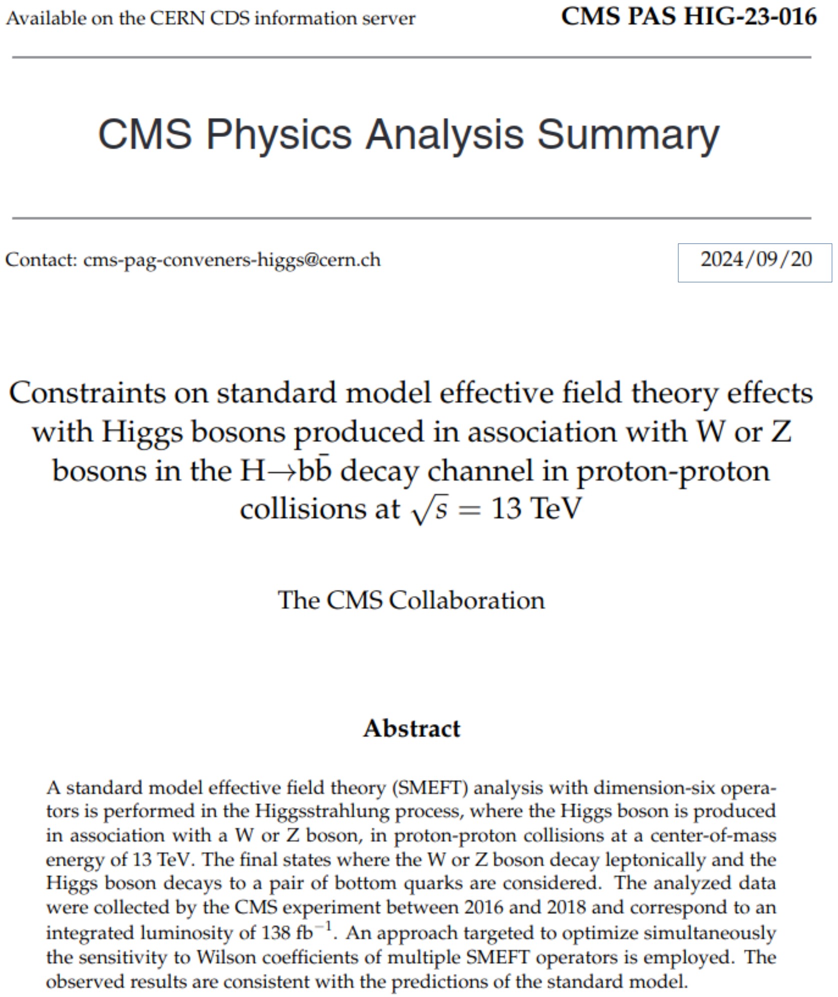
28th October 2024

An implementation of Neural Simulation-Based Inference for Parameter Estimation in ATLAS

The ATLAS Collaboration

Neural Simulation-Based Inference (NSBI) is a powerful class of machine learning (ML)-based methods for statistical inference that naturally handles high-dimensional parameter estimation without the need to bin data into low-dimensional summary histograms. Such methods are promising for a range of measurements, including at the Large Hadron Collider (LHC), where no single observable may be optimal to scan over the entire theoretical phase space under consideration, or where binning data into histograms could result in a loss of sensitivity. This work develops an NSBI framework for statistical inference, using neural networks to estimate probability density ratios, which enables the application of NSBI to a full-scale LHC analysis. It incorporates a large number of systematic uncertainties, quantifies the uncertainty coming from finite training statistics, develops a method to construct confidence intervals, and demonstrates a series of intermediate diagnostic checks that can be performed to validate the robustness of the method. As an example, the power and feasibility of the method are demonstrated on simulated data for a simplified version of an off-shell Higgs boson couplings measurement in the four-leptons final states. This NSBI framework is an extension of the standard statistical framework used by LHC experiments and can benefit a large number of physics analyses.

ATLAS-CONF-2024-015
28 October 2024



Available on the CERN CDS information server **CMS PAS HIG-23-016**

CMS Physics Analysis Summary

Contact: cms-pag-conveners-higgs@cern.ch 2024/09/20

Constraints on standard model effective field theory effects with Higgs bosons produced in association with W or Z bosons in the $\mathrm{H}\to\mathrm{b\bar{b}}$ decay channel in proton-proton collisions at $\sqrt{s} = 13$ TeV

The CMS Collaboration

Abstract

A standard model effective field theory (SMEFT) analysis with dimension-six operators is performed in the Higgsstrahlung process, where the Higgs boson is produced in association with a W or Z boson, in proton-proton collisions at a center-of-mass energy of 13 TeV. The final states where the W or Z boson decay leptonically and the Higgs boson decays to a pair of bottom quarks are considered. The analyzed data were collected by the CMS experiment between 2016 and 2018 and correspond to an integrated luminosity of 138 fb^{-1}. An approach targeted to optimize simultaneously the sensitivity to Wilson coefficients of multiple SMEFT operators is employed. The observed results are consistent with the predictions of the standard model.

ATLAS used simulation-based inference for off-shell H production

Neural network-based approach: arXiv: 2412.01548

Summary

- Detailed effective field theory analysis in Higgs production in association with W/Z boson with full Run 2 data

  - *Follow-up & complementary to cross section measurements*

Documentation
arXiv: 2411.16907
(Accepted in JHEP)

- Probed effects of both vector and gauge coupling operators

- First application of likelihood-free/simulation-based inference at colliders

  - *Developed outside collaboration & technology available for any EFT analysis*

  --- *Road towards fully unbinned EFT analysis using optimal observables* [see Schöfbeck (2024)]

- Results reported as constraints on Wilson coefficients

  - *in 1D with other coefficients profiled or set to SM values*

  - *in 2D with other coefficients profiled or set to SM values*

  ← *findings consistent with SM*

- Best SMEFT sensitivity reported in *VH(bb) channel* till date

Summary

- Detailed effective field theory analysis in Higgs production in association with W/Z boson with full Run 2 data

  - *Follow-up & complementary to cross section measurements*

[Documentation](#)

arXiv: 2411.16907

(Accepted in JHEP)

- Probed effects of both vector and gauge coupling operators

- First application of likelihood-free/simulation-based inference at colliders

  - *Developed outside collaboration & technology available for any EFT analysis*

  --- *Road towards fully unbinned EFT analysis using optimal observables* [see Schöfbeck (2024)]

- Results reported as constraints on Wilson coefficients

  - *in 1D with other coefficients profiled or set to SM values*

  - *in 2D with other coefficients profiled or set to SM values*

  ← *findings consistent with SM*

- Best SMEFT sensitivity reported in *VH(bb) channel* till date

Extra Material

Learning SMEFT likelihood with decision trees (1)

Tree prediction

$$\hat{F}(\mathbf{x}) = \sum_{j\in\mathcal{J}} \mathbb{1}_{\alpha_j}(\mathbf{x}) F_j$$

Phase space partitioning

Prediction

x: Feature vectors

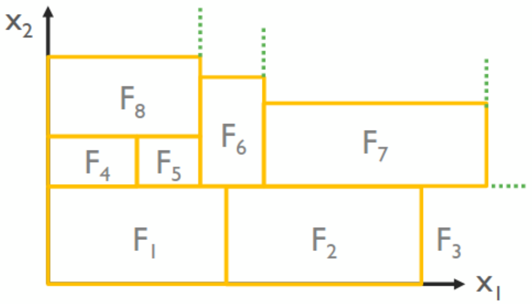
j: Terminal nodes

α_j : Requirements on x for node j

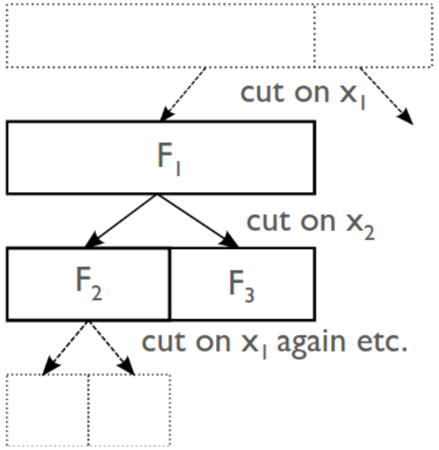
F_j : Prediction for node j

Minimization of loss function w.r.t. α_j and F_j

phase-space partitioning



Training phase



Learning SMEFT likelihood with decision trees (1)

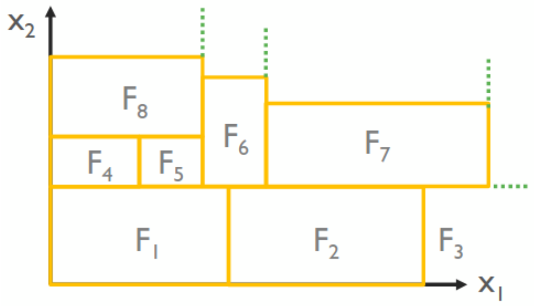
Tree prediction $$\hat{F}(\mathbf{x}) = \sum_{j\in\mathcal{J}} \mathbb{1}_{\alpha_j}(\mathbf{x}) F_j$$

Phase space partitioning

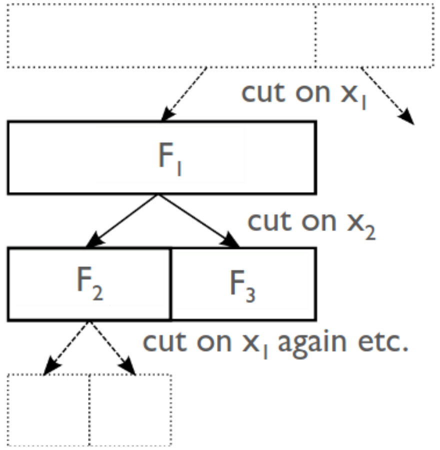
Prediction

x: Feature vectors
j: Terminal nodes
α_j : Requirements on x for node j
F_j : Prediction for node j

phase-space partitioning



Training phase



Minimization of loss function w.r.t. α_j and F_j

Linear term in SMEFT expansion

$$\mathrm{MSE}[\hat{F}_a] = \sum_{j\in\mathcal{J}}\sum_{i\in j} w_i \left|\frac{w_{i,a}}{w_i} - F_j\right|^2 = \sum_{i=1}^{N_{\rm sim}} \frac{w_{i,a}^2}{w_i} - 2\sum_{j\in\mathcal{J}} F_j \sum_{i\in j} w_{i,a} + \sum_{j\in\mathcal{J}} F_j^2 \sum_{i\in j} w_i .$$

Integral replaced by summation

$$\lambda_j = \sum_{i\in j} \omega_i$$

$$\frac{\partial}{\partial F_j}\mathrm{MSE}[\hat{F}_a] = 0 \longrightarrow \qquad F_j = \frac{\sum_{i\in j} w_{i,a}}{\sum_{i\in j} w_i} = \frac{\partial_a \lambda_j}{\lambda_j}\bigg|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} = \partial_a \log\lambda_j\bigg|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

$$\mathrm{MSE}[\hat{F}_a] = -\sum_{j\in\mathcal{J}} \frac{\left(\sum_{i\in j} w_{i,a}\right)^2}{\sum_{i\in j} w_i} = -\sum_{j\in\mathcal{J}} \frac{(\partial_a\lambda_j)^2}{\lambda_j}\bigg|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} = -\sum_{j\in\mathcal{J}} I^{(\lambda_j)}$$ Fisher information for measurement of θ

Fisher information = Variance of score (= derivative of log-likelihood)

Learning SMEFT likelihood with decision trees (1)

Tree prediction $$\hat{F}(\mathbf{x}) = \sum_{j\in\mathcal{J}} \underbrace{\mathbb{1}_{\alpha_j}(\mathbf{x})}_{\text{Phase space partitioning}} \underbrace{F_j}_{\text{Prediction}}$$

x: Feature vectors
j: Terminal nodes
α_j : Requirements on x for node j
F_j : Prediction for node j

Minimization of loss function w.r.t. α_j and F_j

Linear term in SMEFT expansion

$$\mathrm{MSE}[\hat{F}_a] = \sum_{j\in\mathcal{J}}\sum_{i\in j} w_i \left|\frac{w_{i,a}}{w_i} - F_j\right|^2 = \sum_{i=1}^{N_{\mathrm{sim}}} \frac{w_{i,a}^2}{w_i} - 2\sum_{j\in\mathcal{J}} F_j \sum_{i\in j} w_{i,a} + \sum_{j\in\mathcal{J}} F_j^2 \sum_{i\in j} w_i.$$

Integral replaced by summation

$$\lambda_j = \sum_{i\in j} \omega_i$$

$$\frac{\partial}{\partial F_j}\mathrm{MSE}[\hat{F}_a] = 0 \longrightarrow \quad F_j = \frac{\sum_{i\in j} w_{i,a}}{\sum_{i\in j} w_i} = \left.\frac{\partial_a \lambda_j}{\lambda_j}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} = \partial_a \log \lambda_j \Big|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

$$\mathrm{MSE}[\hat{F}_a] = -\sum_{j\in\mathcal{J}} \frac{\left(\sum_{i\in j} w_{i,a}\right)^2}{\sum_{i\in j} w_i} = -\sum_{j\in\mathcal{J}} \left.\frac{(\partial_a \lambda_j)^2}{\lambda_j}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} = -\sum_{j\in\mathcal{J}} I^{(\lambda_j)}$$ Fisher information for measurement of θ

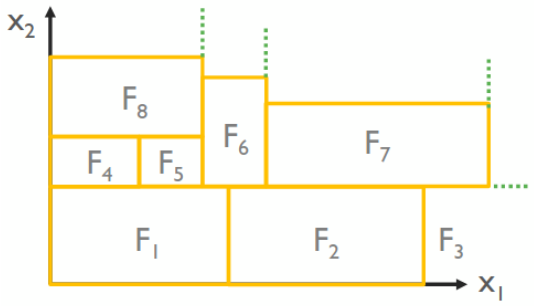
Fisher information = Variance of score (= derivative of log-likelihood)

Cramér-Rao bound: $$\mathrm{Variance}(\hat{\theta}) \geq \frac{1}{I(\theta)}$$ wiki

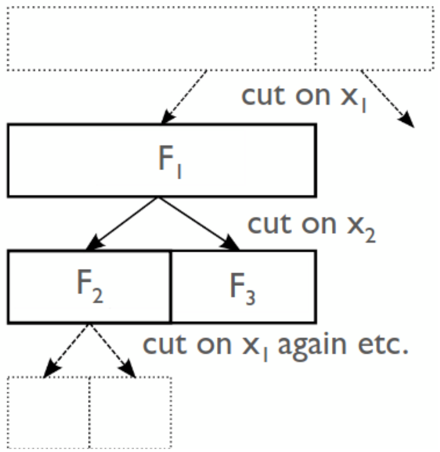
Node-split criterion maximizes Fisher information → Optimal in precision

Starting point of SC, N. Frohner, L. Lechner, R. Schoefbeck, D. Schwarz (2021)

phase-space partitioning



Training phase



Learning SMEFT likelihood with decision trees (1)

Tree prediction $\hat{F}(\mathbf{x}) = \sum_{j\in\mathcal{J}} \mathbb{1}_{\alpha_j}(\mathbf{x}) F_j$

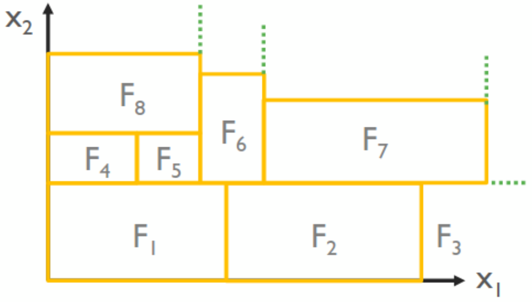
Phase space partitioning

Prediction

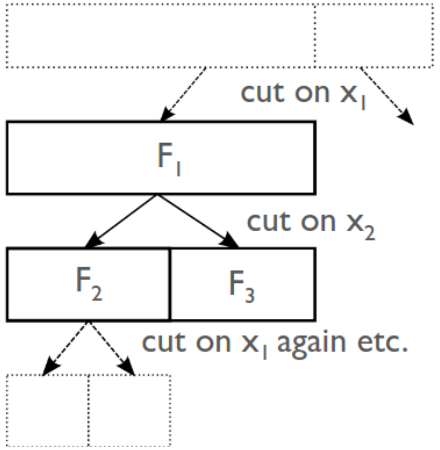
x: Feature vectors
j: Terminal nodes
α_j : Requirements on x for node j
F_j : Prediction for node j

Minimization of loss function w.r.t. α_j and F_j

phase-space partitioning



Training phase



Linear term in SMEFT expansion

$$\mathrm{MSE}[\hat{F}_a] = \sum_{j\in\mathcal{J}} \sum_{i\in j} w_i \left| \frac{w_{i,a}}{w_i} - F_j \right|^2 = \sum_{i=1}^{N_{\mathrm{sim}}} \frac{w_{i,a}^2}{w_i} - 2 \sum_{j\in\mathcal{J}} F_j \sum_{i\in j} w_{i,a} + \sum_{j\in\mathcal{J}} F_j^2 \sum_{i\in j} w_i .$$

Integral replaced by summation

$$\lambda_j = \sum_{i\in j} \omega_i$$

$$\frac{\partial}{\partial F_j} \mathrm{MSE}[\hat{F}_a] = 0 \longrightarrow \qquad F_j = \frac{\sum_{i\in j} w_{i,a}}{\sum_{i\in j} w_i} = \left.\frac{\partial_a \lambda_j}{\lambda_j}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} = \partial_a \log \lambda_j \Big|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

$$\mathrm{MSE}[\hat{F}_a] = -\sum_{j\in\mathcal{J}} \frac{\left(\sum_{i\in j} w_{i,a}\right)^2}{\sum_{i\in j} w_i} = -\sum_{j\in\mathcal{J}} \left.\frac{(\partial_a \lambda_j)^2}{\lambda_j}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} = -\sum_{j\in\mathcal{J}} I^{(\lambda_j)}$$

Fisher information for measurement of θ

Fisher information = Variance of score (= derivative of log-likelihood)

Cramér-Rao bound: $\mathrm{Variance}(\hat{\theta}) \geq \frac{1}{I(\theta)}$ wiki

Node-split criterion maximizes Fisher information → Optimal in precision

Starting point of SC, N. Frohner, L. Lechner, R. Schoefbeck, D. Schwarz (2021)

$$\lambda_j = b_j + \theta s_j \qquad \rho_j = \frac{\theta s_j}{b_j + \theta s_j}$$

$$L = -\sum_j \frac{(\partial_\theta \lambda_j)^2}{\lambda_j} = -\sum_j \frac{s_j^2}{b_j + \theta s_j} = -\frac{1}{\theta^2} \sum_j \lambda_j \rho^2 \equiv \sum_j \lambda_j \rho (1-\rho)$$

Gini index implemented in TMVA for classification

Learning SMEFT likelihood with decision trees (1)

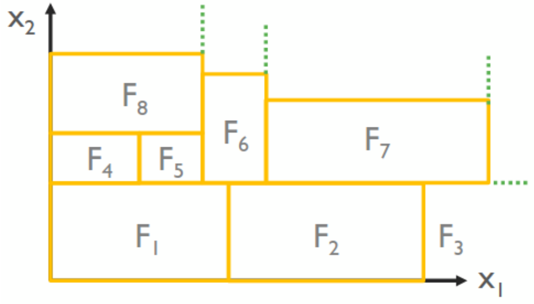
Tree prediction $\hat{F}(\mathbf{x}) = \sum_{j\in\mathcal{J}} \mathbb{1}_{\alpha_j}(\mathbf{x}) F_j$

Phase space partitioning

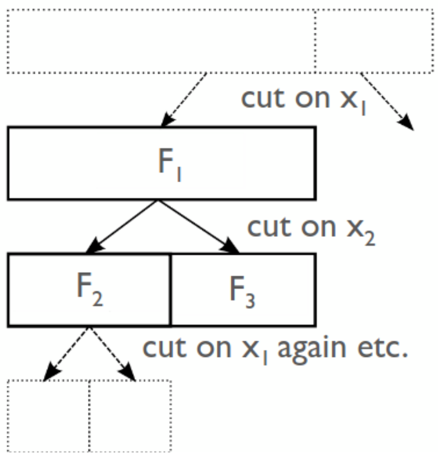
Prediction

x: Feature vectors
j: Terminal nodes
α_j : Requirements on x for node j
F_j : Prediction for node j

phase-space partitioning



Training phase



Minimization of loss function w.r.t. α_j and F_j

Linear term in SMEFT expansion

$$\text{MSE}[\hat{F}_a] = \sum_{j\in\mathcal{J}}\sum_{i\in j} w_i \left|\frac{w_{i,a}}{w_i} - F_j\right|^2 = \sum_{i=1}^{N_{\text{sim}}} \frac{w_{i,a}^2}{w_i} - 2\sum_{j\in\mathcal{J}} F_j \sum_{i\in j} w_{i,a} + \sum_{j\in\mathcal{J}} F_j^2 \sum_{i\in j} w_i.$$

Integral replaced by summation

$$\lambda_j = \sum_{i\in j} \omega_i$$

$$\frac{\partial}{\partial F_j}\text{MSE}[\hat{F}_a] = 0 \longrightarrow \qquad F_j = \frac{\sum_{i\in j} w_{i,a}}{\sum_{i\in j} w_i} = \left.\frac{\partial_a \lambda_j}{\lambda_j}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} = \partial_a \log \lambda_j\Big|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

$$\text{MSE}[\hat{F}_a] = -\sum_{j\in\mathcal{J}} \frac{\left(\sum_{i\in j} w_{i,a}\right)^2}{\sum_{i\in j} w_i} = -\sum_{j\in\mathcal{J}} \left.\frac{(\partial_a \lambda_j)^2}{\lambda_j}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0} = -\sum_{j\in\mathcal{J}} I^{(\lambda_j)}$$

Fisher information for measurement of θ

Fisher information = Variance of score (= derivative of log-likelihood)

Quadratic term in SMEFT expansion

$$F_j = \frac{\sum_{i\in j} w_{i,ab}}{\sum_{i\in j} w_i} = \left.\frac{\partial_a\partial_b \lambda_j}{\lambda_j}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}.$$

$$\text{MSE}[\hat{F}_{ab}] = -\sum_{j\in\mathcal{J}} \frac{\left(\sum_{i\in j} w_{i,ab}\right)^2}{\sum_{i\in j} w_i} = -\sum_{j\in\mathcal{J}} \left.\frac{(\partial_a\partial_b \lambda_j)^2}{\lambda_j}\right|_{\boldsymbol{\theta}=\boldsymbol{\theta}_0}$$

Cramér-Rao bound: $\text{Variance}(\hat{\theta}) \geq \frac{1}{I(\theta)}$ wiki

Node-split criterion maximizes Fisher information → Optimal in precision

$$\lambda_j = b_j + \theta s_j \qquad \rho_j = \frac{\theta s_j}{b_j + \theta s_j}$$

$$L = -\sum_j \frac{(\partial_\theta \lambda_j)^2}{\lambda_j} = -\sum_j \frac{s_j^2}{b_j + \theta s_j} = -\frac{1}{\theta^2}\sum_j \lambda_j \rho^2 \equiv \sum_j \lambda_j \rho(1-\rho)$$

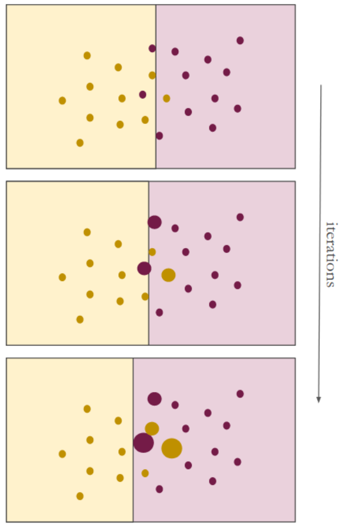
Starting point of SC, N. Frohner, L. Lechner, R. Schoefbeck, D. Schwarz (2021)

Gini index implemented in TMVA for classification

Learning SMEFT likelihood with decision trees (2)

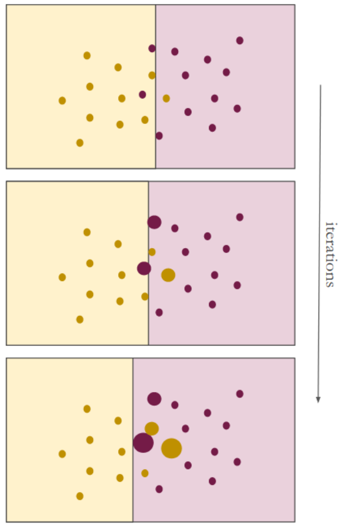
Boosting: Provides a strong learner by iteratively training an ensemble of weak learners to pseudo-residuals of previous iteration

$\hat{F}^b(x) = \hat{f}^b(x) + \eta\hat{F}^{b-1}(x)$ Minimize loss function loss w.r.t. *f(x)* ← Goes on till a pre-defined number B



Learning SMEFT likelihood with decision trees (2)

Boosting: Provides a strong learner by iteratively training an ensemble of weak learners to pseudo-residuals of previous iteration



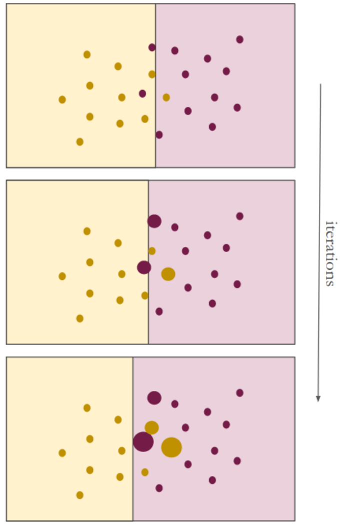
$\hat{F}^b(\boldsymbol{x}) = \hat{f}^b(\boldsymbol{x}) + \eta \hat{F}^{b-1}(\boldsymbol{x})$ Minimize loss function loss w.r.t. *f(x)* ← Goes on till a pre-defined number B

$$\mathrm{MSE}[\hat{F}_a] = \sum_{j\in\mathcal{J}}\sum_{i\in j} w_i \left|\frac{w_{i,a}}{w_i} - \hat{f}^b(\boldsymbol{x}) - \eta\hat{F}^{b-1}(\boldsymbol{x})\right|^2 = \sum_{j\in\mathcal{J}}\sum_{i\in j} w_i \left|\frac{w_{i,a} - \eta\hat{F}^{b-1}(\boldsymbol{x})w_i}{w_i} - \hat{f}^b(\boldsymbol{x})\right|^2$$

Weak learner needs to fit w - ηF ← Target needs to be updated in each iteration

Learning SMEFT likelihood with decision trees (2)

Boosting: Provides a strong learner by iteratively training an ensemble of weak learners to pseudo-residuals of previous iteration



$$\hat{F}^b(\boldsymbol{x}) = \hat{f}^b(\boldsymbol{x}) + \eta \hat{F}^{b-1}(\boldsymbol{x})$$

Minimize loss function loss w.r.t. *f(x)* ← Goes on till a pre-defined number B

$$\text{MSE}[\hat{F}_a] = \sum_{j\in\mathcal{J}} \sum_{i\in j} w_i \left| \frac{w_{i,a}}{w_i} - \hat{f}^b(\boldsymbol{x}) - \eta \hat{F}^{b-1}(\boldsymbol{x}) \right|^2 = \sum_{j\in\mathcal{J}} \sum_{i\in j} w_i \left| \frac{w_{i,a} - \eta \hat{F}^{b-1}(\boldsymbol{x}) w_i}{w_i} - \hat{f}^b(\boldsymbol{x}) \right|^2$$

Weak learner needs to fit w - ηF ← Target needs to be updated in each iteration

Final outcome of algorithm

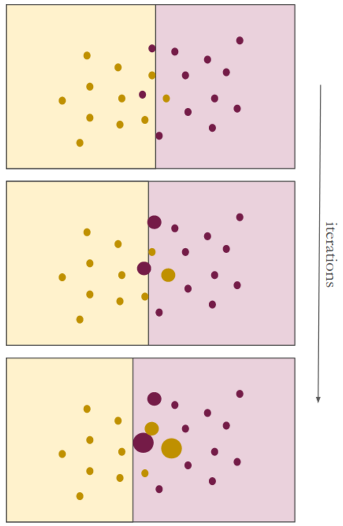
$$\hat{R}(\boldsymbol{x}|\boldsymbol{\theta}, \boldsymbol{\theta}_0) = 1 + (\theta - \theta_0)_a \hat{F}_a^{(B)}(\boldsymbol{x}) + \frac{1}{2}(\theta - \theta_0)_a (\theta - \theta_0)_b \hat{F}_{ab}^{(B)}(\boldsymbol{x})$$

Boosted information tree (BIT)

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Learning SMEFT likelihood with decision trees (2)

Boosting: Provides a strong learner by iteratively training an ensemble of weak learners to pseudo-residuals of previous iteration



$\hat{F}^b(\boldsymbol{x}) = \hat{f}^b(\boldsymbol{x}) + \eta \hat{F}^{b-1}(\boldsymbol{x})$ Minimize loss function loss w.r.t. *f(x)* ← Goes on till a pre-defined number B

$$\mathrm{MSE}[\hat{F}_a] = \sum_{j\in\mathcal{J}}\sum_{i\in j} w_i \left|\frac{w_{i,a}}{w_i} - \hat{f}^b(\boldsymbol{x}) - \eta\hat{F}^{b-1}(\boldsymbol{x})\right|^2 = \sum_{j\in\mathcal{J}}\sum_{i\in j} w_i \left|\frac{w_{i,a} - \eta\hat{F}^{b-1}(\boldsymbol{x})w_i}{w_i} - \hat{f}^b(\boldsymbol{x})\right|^2$$

Weak learner needs to fit w - ηF ← Target needs to be updated in each iteration

Final outcome of algorithm $\hat{R}(\boldsymbol{x}|\boldsymbol{\theta},\boldsymbol{\theta}_0) = 1 + (\theta-\theta_0)_a \hat{F}_a^{(B)}(\boldsymbol{x}) + \frac{1}{2}(\theta-\theta_0)_a(\theta-\theta_0)_b\hat{F}_{ab}^{(B)}(\boldsymbol{x})$ Boosted information tree (BIT)

SC, S. Roshap, R. Schoefbeck, D. Schwarz (2022)

Separate training for each linear (‘a’) & quadratic terms (‘ab’) → Total # of trainings = n + n(n+1)/2

LLR to achieve

$$q(\mathcal{D}(N_{\text{obs}},\boldsymbol{x})|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0) = -2\left[\mathcal{L}(\sigma(\boldsymbol{\theta}_1)-\sigma(\boldsymbol{\theta}_0)) - \sum_{i=1}^{N_{\text{obs}}}\ln R(\boldsymbol{x}|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0)\right]$$

=
(in large sample limit)

LLR obtained

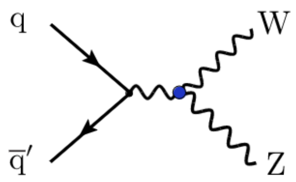
$$\hat{q}(\mathcal{D}(N_{\text{obs}},\boldsymbol{x})|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0) = -2\left[\mathcal{L}(\sigma(\boldsymbol{\theta}_1)-\sigma(\boldsymbol{\theta}_0)) - \sum_{i=1}^{N_{\text{obs}}}\ln \hat{R}(\boldsymbol{x}|\boldsymbol{\theta}_1,\boldsymbol{\theta}_0)\right]$$

Simulation strategy for SMEFT

Possible to encode SMEFT prediction in event weights $\omega = \frac{|\mathcal{M}_{SMEFT}(c = c_1)|^2}{|\mathcal{M}_{SMEFT}(c = c_0)|^2}$

$$\omega(\boldsymbol{z}|\boldsymbol{c}) \sim \frac{d\sigma}{dz} = \mathrm{Const}(\boldsymbol{z}) + \mathrm{LIN}_a(\boldsymbol{z})c_a + \frac{1}{2}\mathrm{QUAD}_{ab}(\boldsymbol{z})c_a c_b$$

Store N(n) weights per event → obtain EFT prediction for any coefficient value



→ EFT operator changes helicity configuration

SM: +-/-+ EFT: ++/--

Helicity-aware reweighting $\omega = \frac{|\mathcal{M}(z_p, h|c_1)|^2}{|\mathcal{M}(z_p, h|c_0)|^2}$

Needs careful choice of reference point

Helicity-ignorant reweighting $\omega = \frac{\sum_h |\mathcal{M}(z_p, h|c_1)|^2}{\sum_h |\mathcal{M}(z_p, h|c_0)|^2}$

Robust option

SC & others (2024)