2007.10356

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2308.05704

Applications of Likelihood Learning

Benasque 2023

Alfredo Glioti & Jaco ter Hoeve

IPhT & VU Amsterdam

Recap: likelihood ratio from ML

- Starting from two balanced datasets $\mathscr{D}_{\mathrm{SM}}$ and $\mathscr{D}_{\mathrm{EFT}}$ drawn from $f(\boldsymbol{x}\,|\,\mathrm{SM})$ and $f(\boldsymbol{x}\,|\,\mathrm{EFT})$, we minimise e.g. the cross-entropy loss

$$L[g(\boldsymbol{x})] = -\frac{1}{N}\sum_{e\in\mathscr{D}_{\mathrm{EFT}}} w_e \log(1-g(\boldsymbol{x}_e)) - \frac{1}{N}\sum_{\mathscr{D}_{\mathrm{SM}}} w_e \log g(\boldsymbol{x}_e)$$

$\{m_{t\bar{t}}, \eta_l, \Delta\phi, \dots\}$

Event weights

- The learned decision boundary $g(\boldsymbol{x})$ is one-to-one with the likelihood ratio (LR) as $N \to \infty$

$$\frac{\delta L}{\delta g} = 0 \implies \hat{g}(\boldsymbol{x}) = \left(1 + \frac{f(\boldsymbol{x}\,|\,\mathrm{EFT})}{f(\boldsymbol{x}\,|\,\mathrm{SM})}\right)^{-1} \equiv \frac{1}{1+r(\boldsymbol{x})}$$

Parameterise with NNs

The experimental pipeline

We are progressively moving through the simulation chain (latent space)

$$p(x|c) \sim \int dz_{\text{det}} dz_{\text{shower}} dz_{\text{parton}} p(x|z_{\text{det}}) p(z_{\text{det}}|z_{\text{shower}}) p(z_{\text{shower}}|z_{\text{parton}}) p(z_{\text{parton}}|c)$$

DELPHES fast simulation

SMEFT@NLO

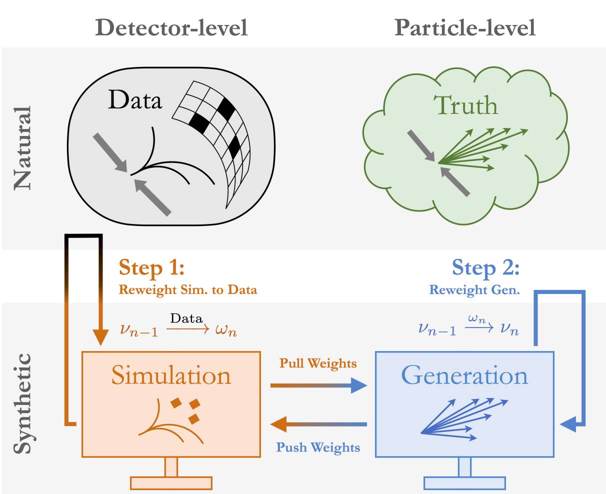
(Likelihood free) Inference Observed $\longrightarrow$ Hidden/latent variables $\longrightarrow$ POI

Generation Observed $\longleftarrow$ Hidden/latent variables $\longleftarrow$ POI

The experimental pipeline

We are progressively moving through the simulation chain (latent space)

$$p(x|c) \sim \int dz_{\text{det}} dz_{\text{shower}} dz_{\text{parton}} p(x|z_{\text{det}}) p(z_{\text{det}}|z_{\text{shower}}) p(z_{\text{shower}}|z_{\text{parton}}) p(z_{\text{parton}}|c)$$



Unbinned unfolding, Omnifold [1911.09107]

SMEFT@NLO

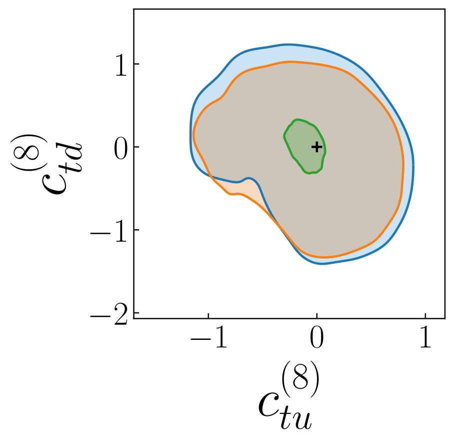
(Likelihood free) Inference	Observed	→	Hidden/latent variables	→ POI
Generation	Observed	←	Hidden/latent variables	← POI

Why interesting for us?

- Global efforts **reinterpret** existing "SM measurements" in an EFT context
- But which measurements are the most **sensitive** to EFT parameters?
  - Inclusive, single to multi-differential (which variables)
  - Binned or unbinned, which binning?

Framework needed to integrate unbinned multivariate observables into **global** SMEFT fits

- **Optimal** bounds on the EFT parameters
- Useful **diagnosis tool** to assess information loss



Applications of likelihood learning

Focusses on global EFT fits

Nikhef-2022-015

Unbinned multivariate observables for global SMEFT analyses from machine learning

Raquel Gomez Ambrosio,[1,2] Jaco ter Hoeve,[3,4] Maeve Madigan,[5] Juan Rojo,[3,4] and Veronica Sanz[6,7]

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Abstract

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1

Reweighting for more accurate learning

Boosting likelihood learning with event reweighting

Siyu Chen[1], Alfredo Glioti[2], Giuliano Panico[3,4], and Andrea Wulzer[5,6]

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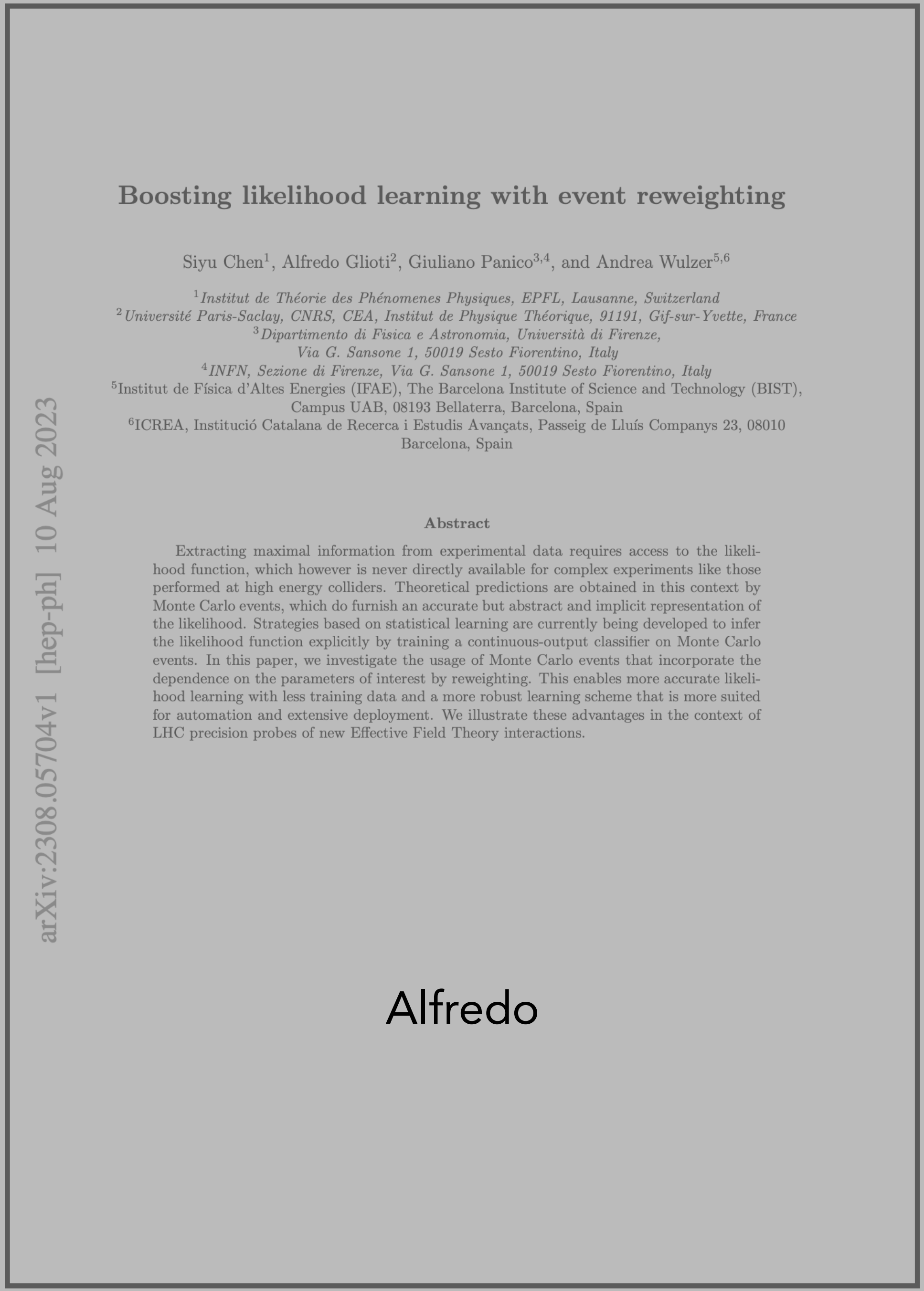

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Alfredo

The ML4EFT framework

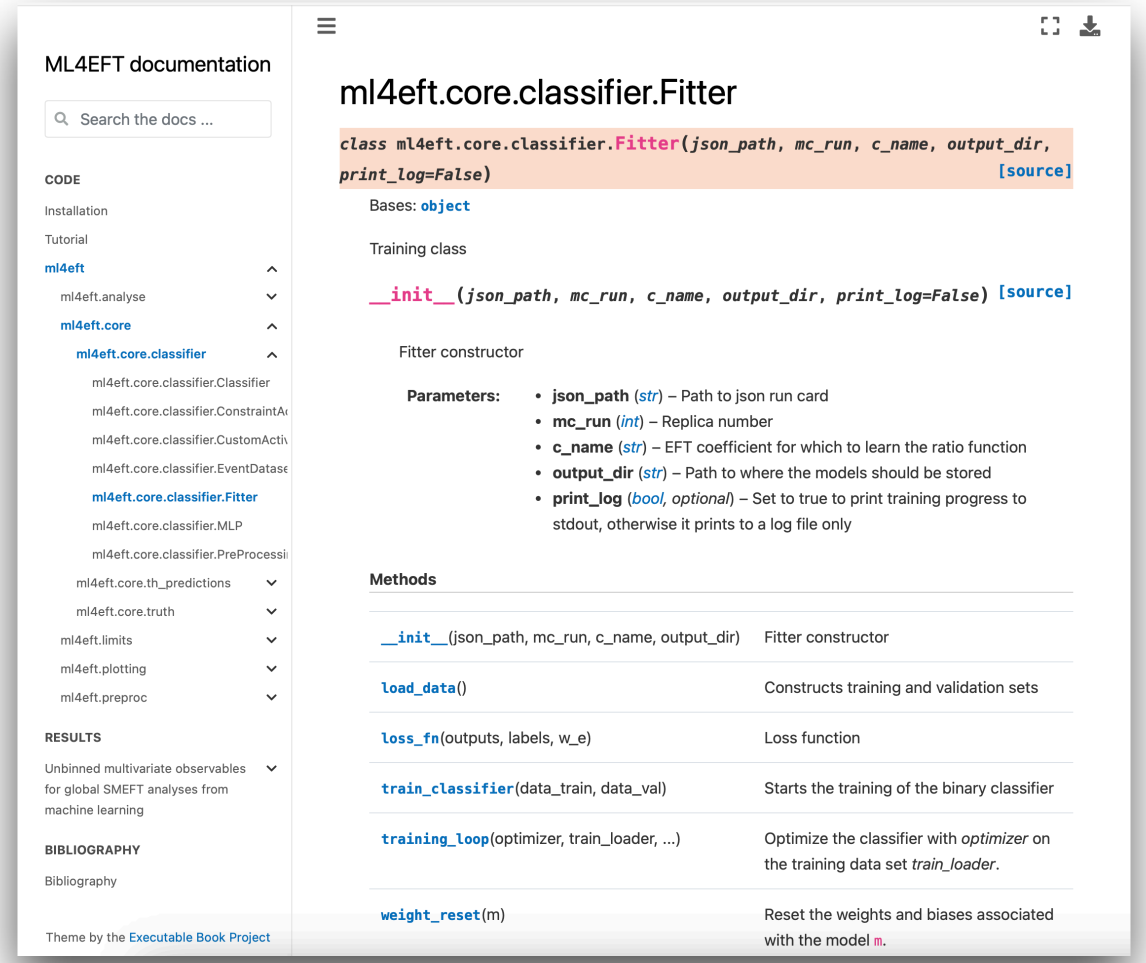
`pip install ml4eft`

https://lhcfitnikhef.github.io/ML4EFT

2211.02058 R. Gomez Ambrosio, JtH, M. Madigan, J. Rojo, V.Sanz

Open-source NN-based python framework for the integration of unbinned multivariate observables into global SMEFT fits

- **Goal**: provide optimal constraints on the SMEFT
- **Diagnostic tool:** what is the information loss incurred by a particular choice of bins?
- **Projections:** how will SMEFT constraints improve if unbinned data are made available?



Modular structure, easy to maintain, well documented

Anticipating global fits

- Global EFT fits typically feature ~50 WCs and thus efficient scaling with the number of WCs becomes essential

- **ML4EFT 1.0:** learn the coefficient functions separately and combine afterwards

Assumes no sign flips in interferences
Fix is part of **ML4EFT2.0**

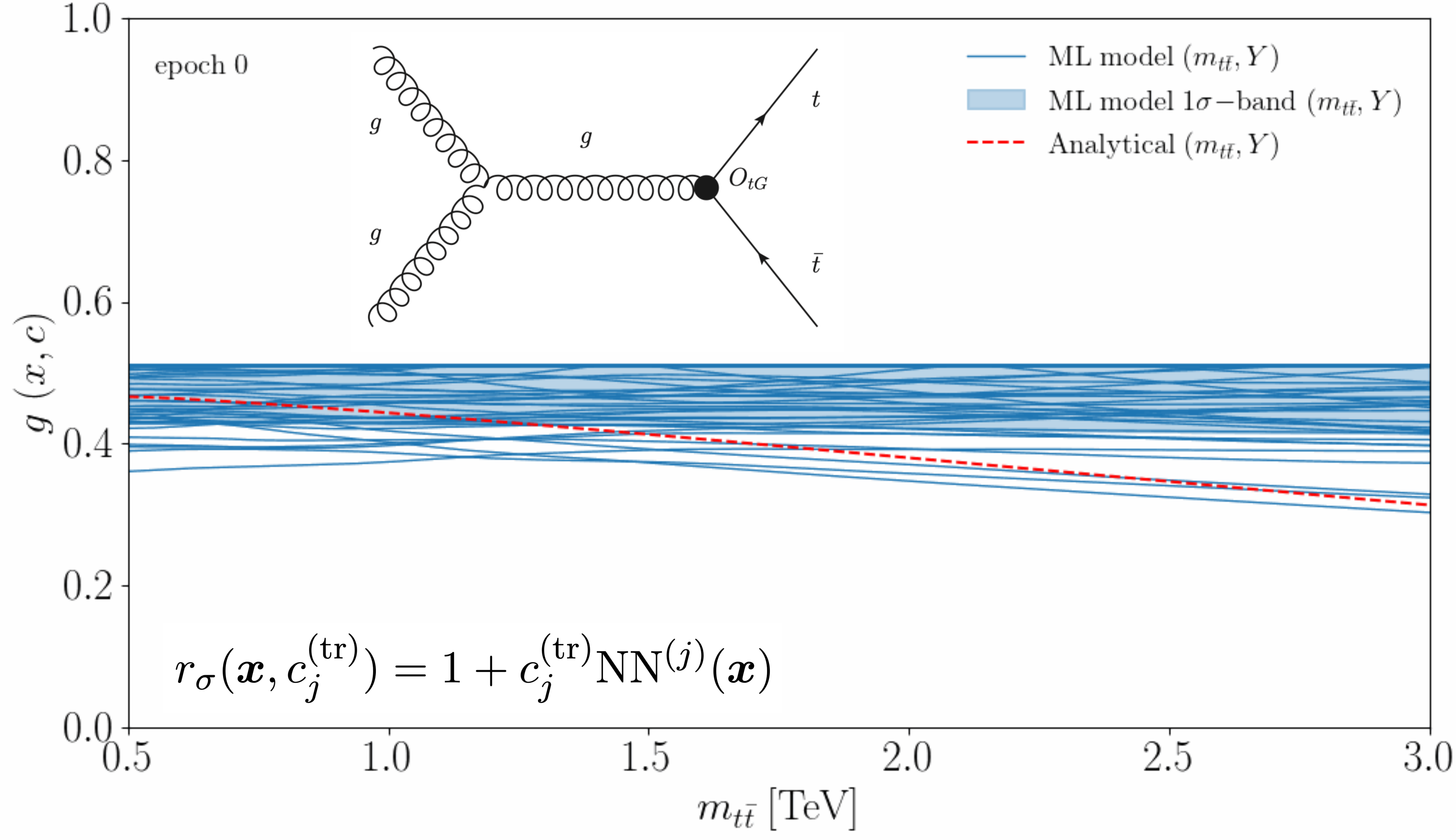
$$r(\boldsymbol{x}, \boldsymbol{c}) = 1 + \sum_{j=1}^{n_{\rm eft}} r^{(j)}(\boldsymbol{x}) c_j + \sum_{j=1}^{n_{\rm eft}} \sum_{k \geq j}^{n_{\rm eft}} r^{(j,k)}(\boldsymbol{x}) c_j c_k$$

Example: to learn a single $r^{(j)}$, generate $\mathscr{D}_{\rm sm}$ and $\mathscr{D}_{\rm eft}$ at c_j up to $\mathcal{O}(\Lambda^{-2})$. Then $r(\boldsymbol{x}, \boldsymbol{c}) = 1 + r^{(j)}(\boldsymbol{x}) c_j^{(\rm tr)}$ and training means

$$g(\boldsymbol{x}, c_j^{(\rm tr)}) = \left(1 + \left[1 + c_j^{(\rm tr)} \cdot \mathrm{NN}^{(j)}(\boldsymbol{x})\right]\right)^{-1} \qquad \mathrm{NN}^{(j)}(\boldsymbol{x}) \to r^{(j)}(\boldsymbol{x})$$

Toy example

$$L[g(\boldsymbol{x},\boldsymbol{c})] = -\frac{1}{N}\sum_{e\in\mathcal{D}_{\rm eft}} w_e \log(1-g(\boldsymbol{x}_e,\boldsymbol{c})) - \frac{1}{N}\sum_{e\in\mathcal{D}_{\rm sm}} w_e \log g(\boldsymbol{x}_e,\boldsymbol{c})$$



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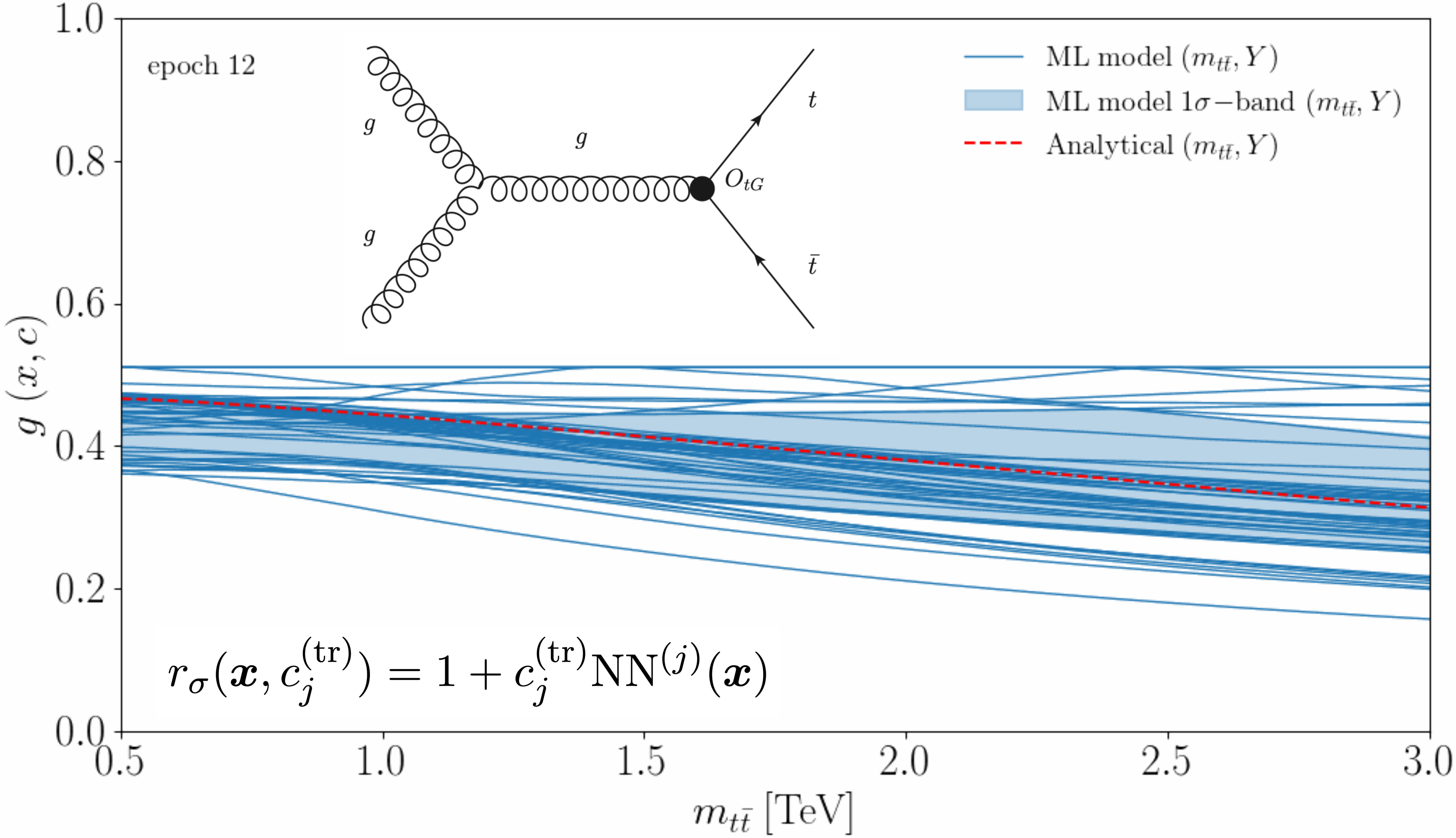

$$r_\sigma(\boldsymbol{x}, c_j^{(\rm tr)}) = 1 + c_j^{(\rm tr)}\mathrm{NN}^{(j)}(\boldsymbol{x})$$

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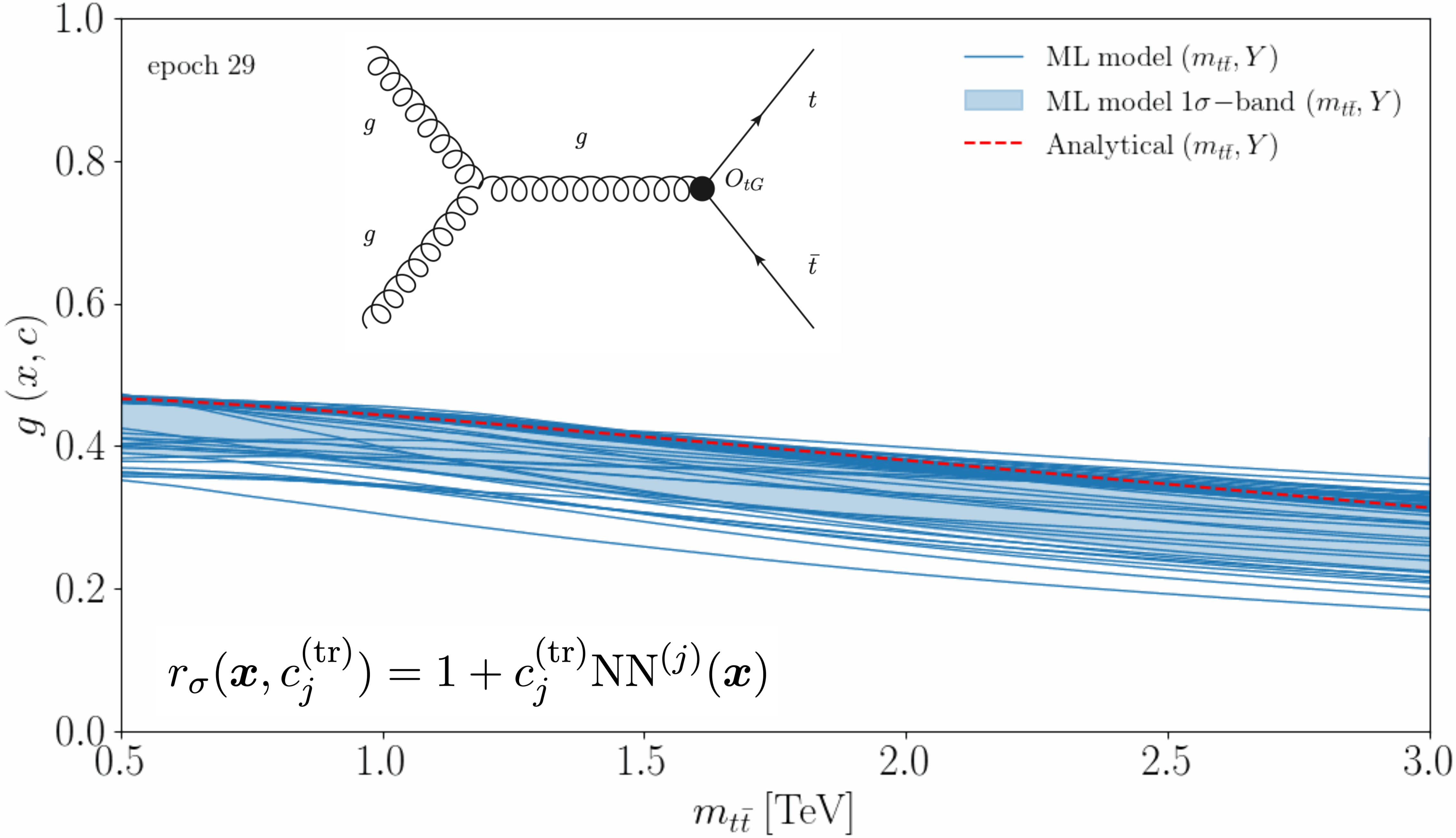

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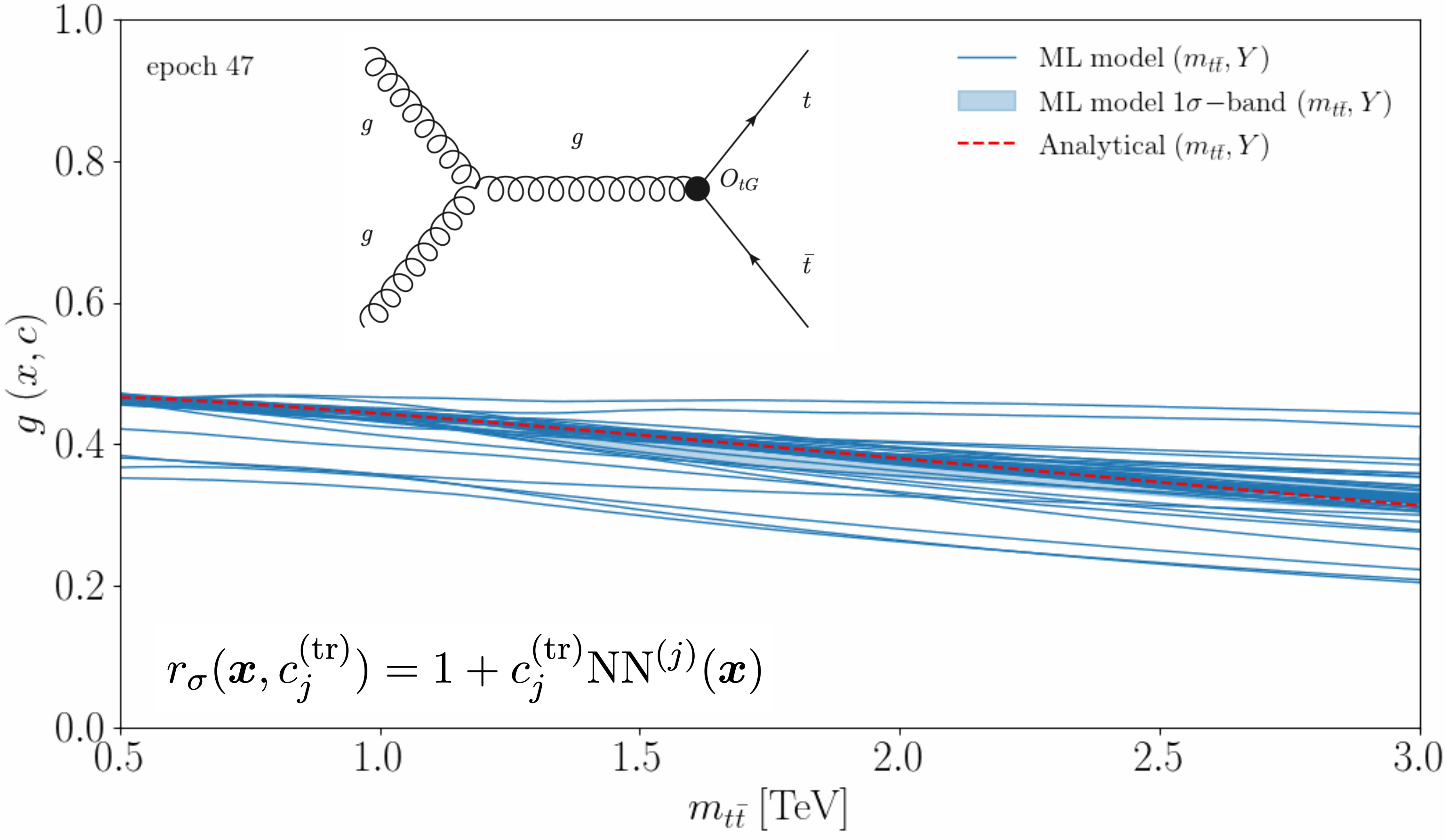

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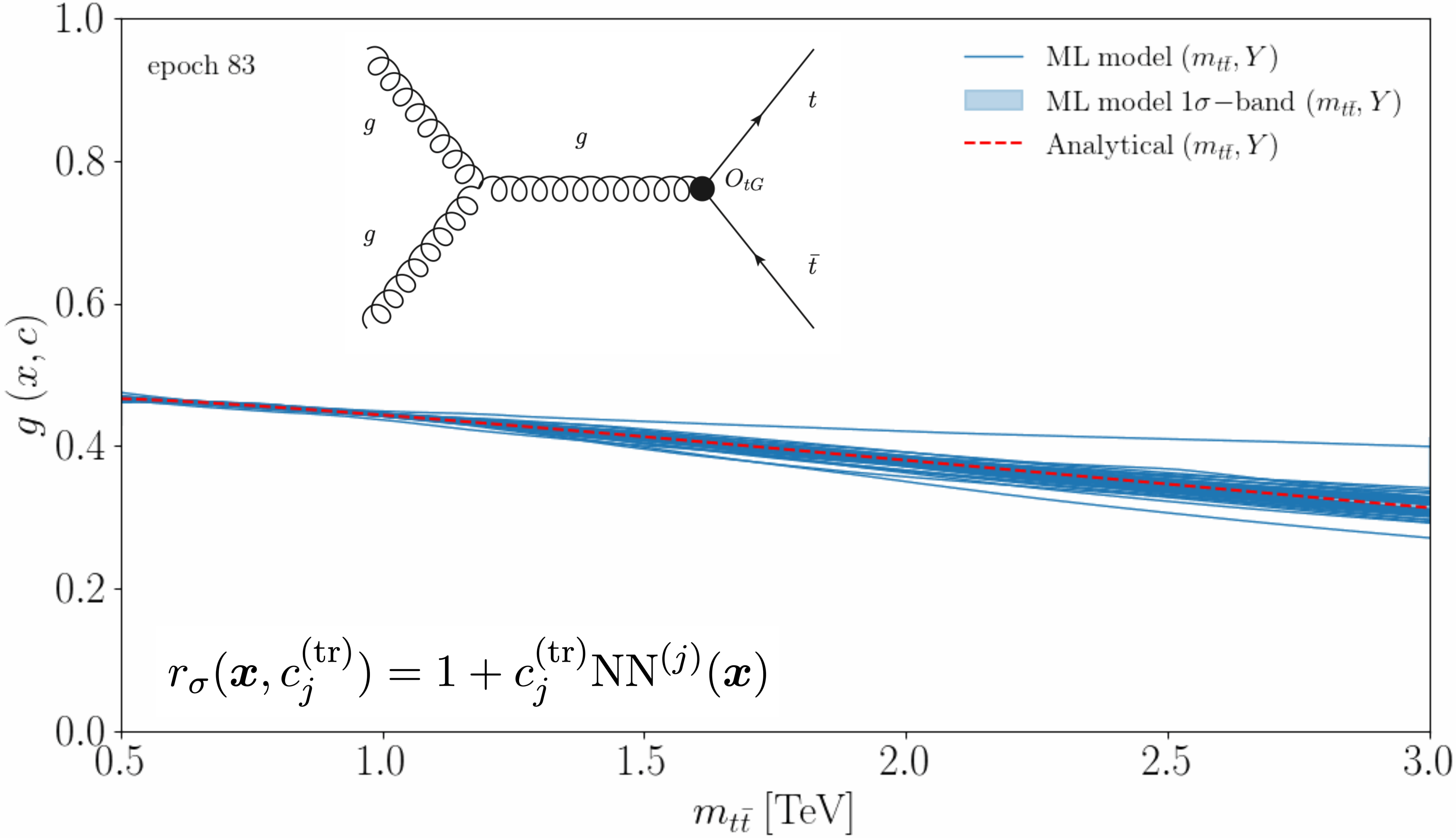

Toy example

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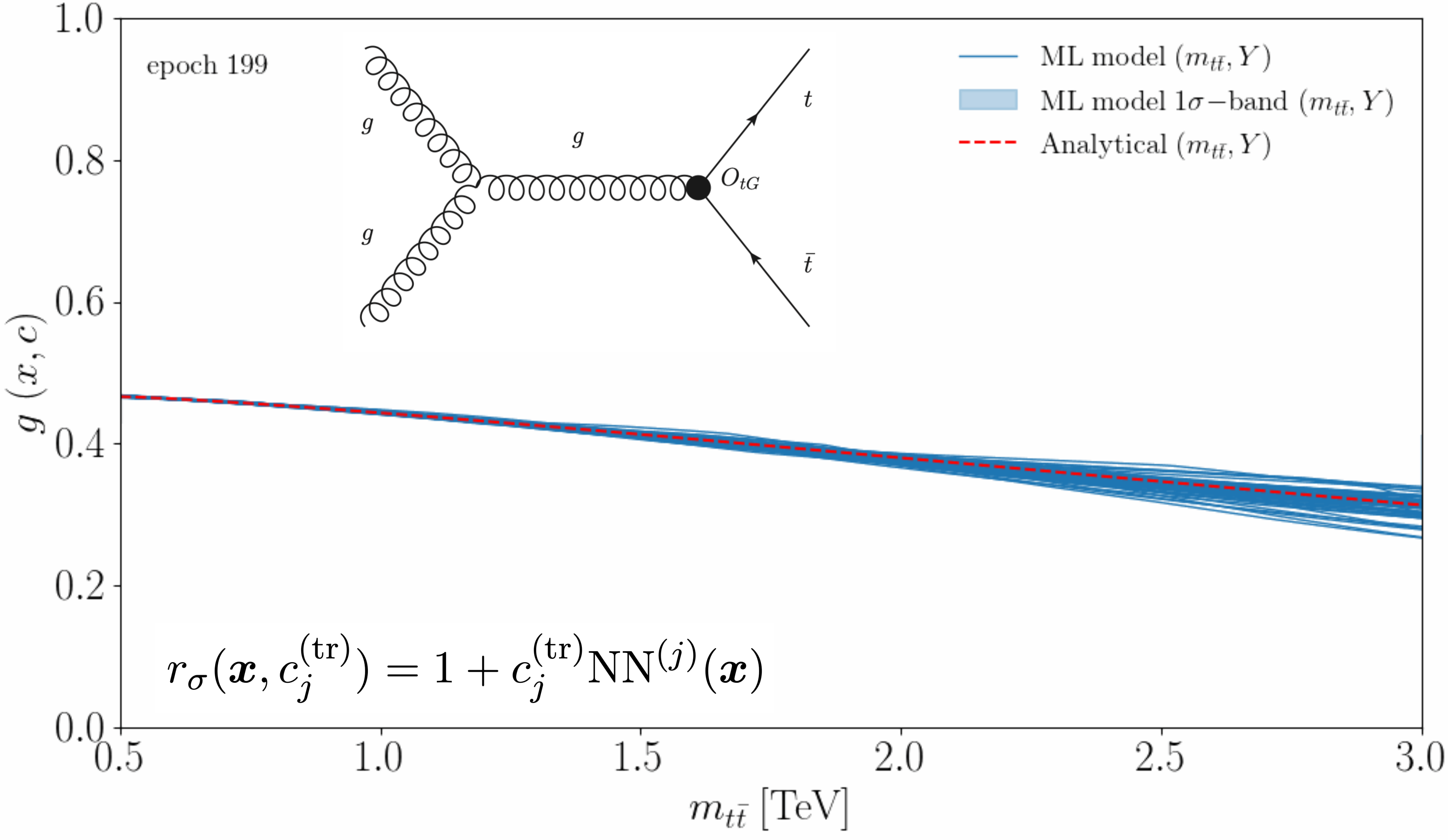
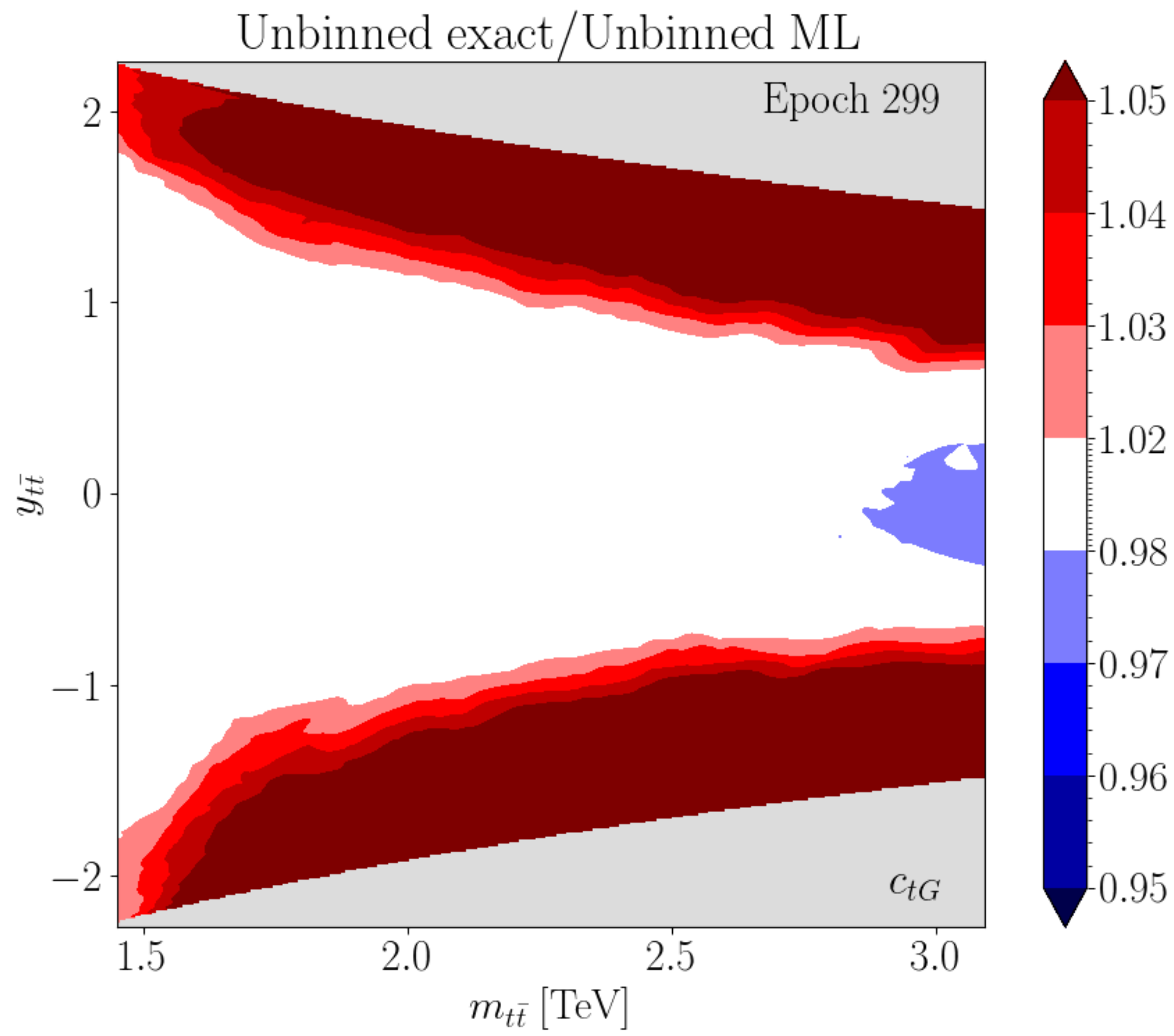
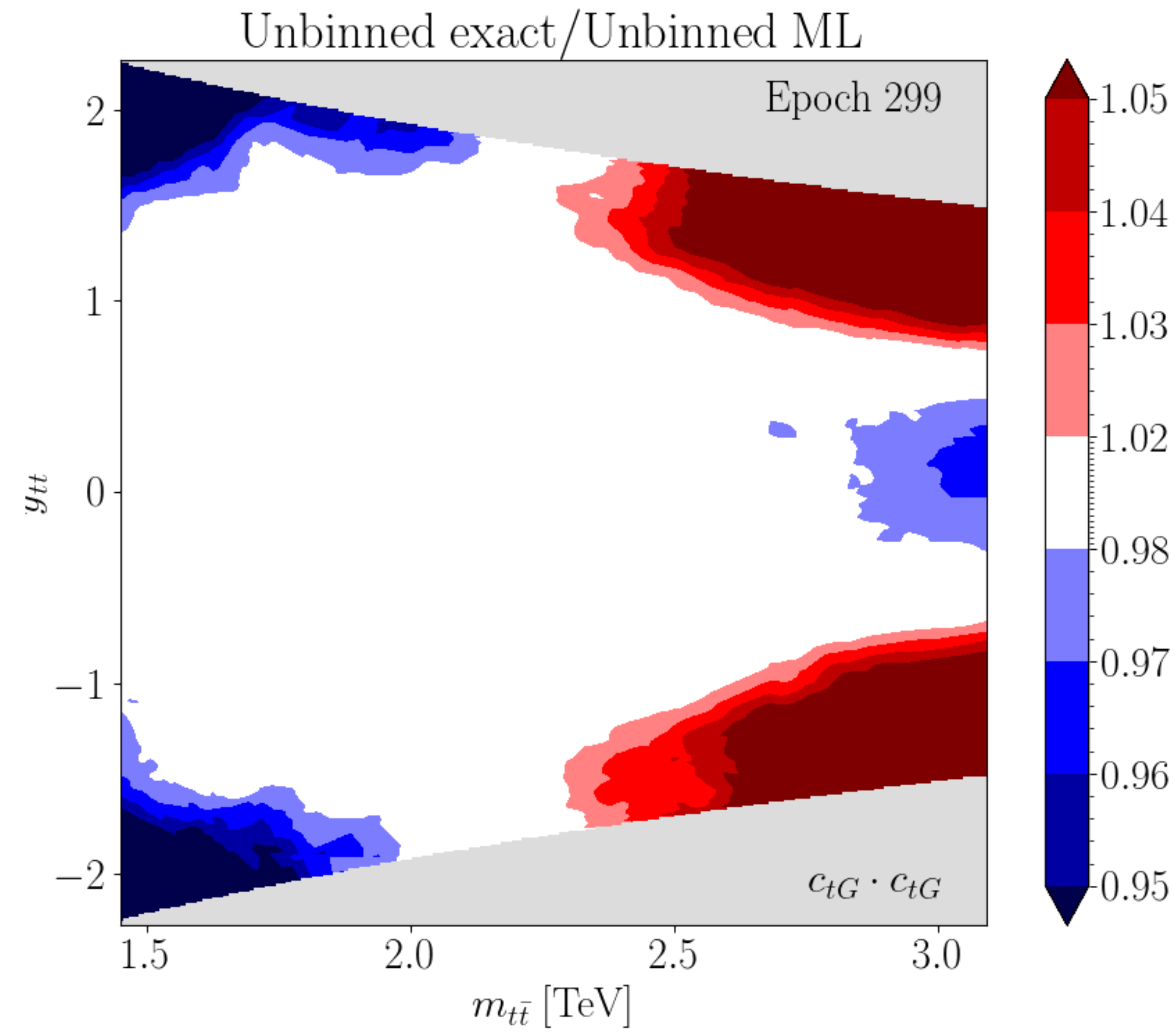


$$r_\sigma(\boldsymbol{x}, c_j^{(\text{tr})}) = 1 + c_j^{(\text{tr})} \text{NN}^{(j)}(\boldsymbol{x})$$

Toy example

2 kinematic features

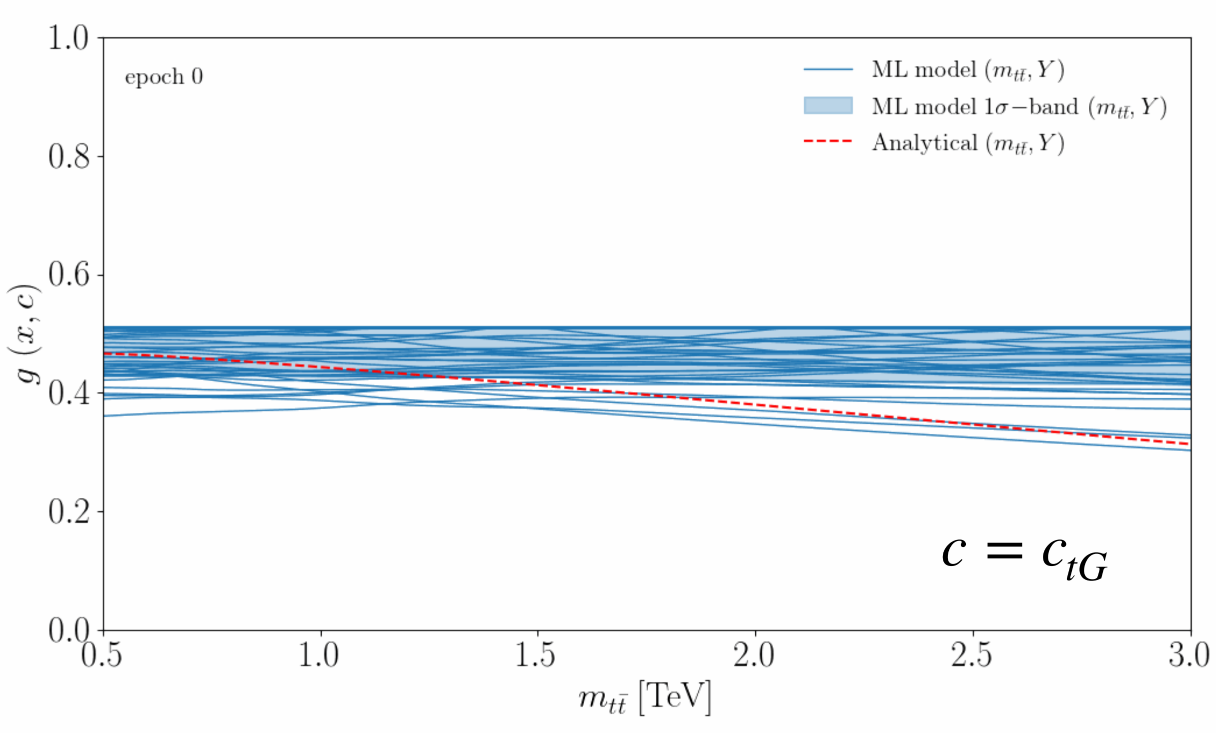




Uncertainty treatment

- We only have finite training data and NNs are subject to methodological uncertainties
- Propagate uncertainties as well as finite training set effects to the space of models by training multiple replicas

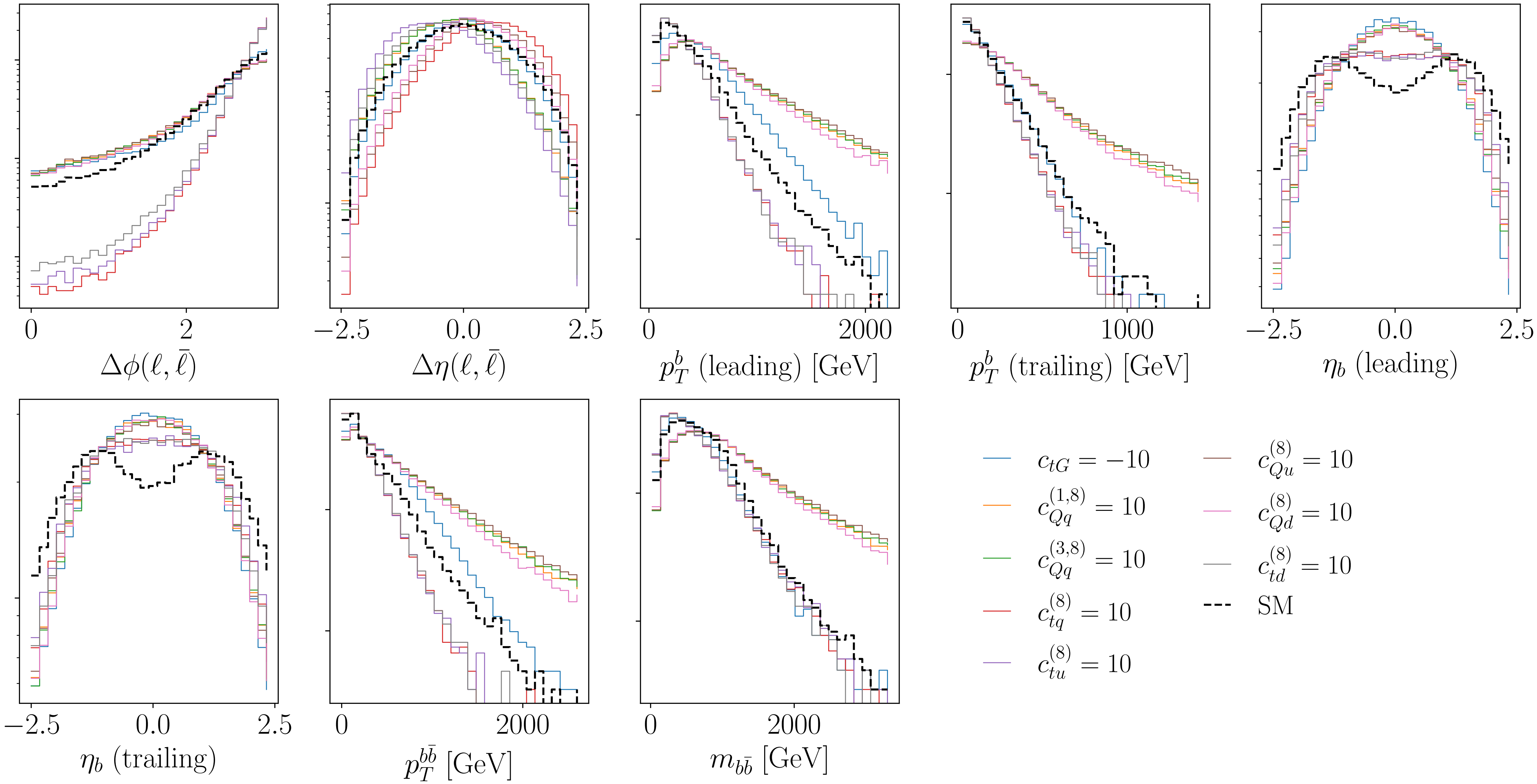
$$\hat{r}^{(i)}(\boldsymbol{x}, \boldsymbol{c}) \equiv 1 + \sum_{j=1}^{n_{\mathrm{eft}}} \mathrm{NN}_i^{(j)}(\boldsymbol{x}) c_j + \sum_{j=1}^{n_{\mathrm{eft}}} \sum_{k \geq j}^{n_{\mathrm{eft}}} \mathrm{NN}_i^{(j,k)}(\boldsymbol{x}) c_j c_k \,, \qquad i = 1, \ldots, N_{\mathrm{rep}}$$



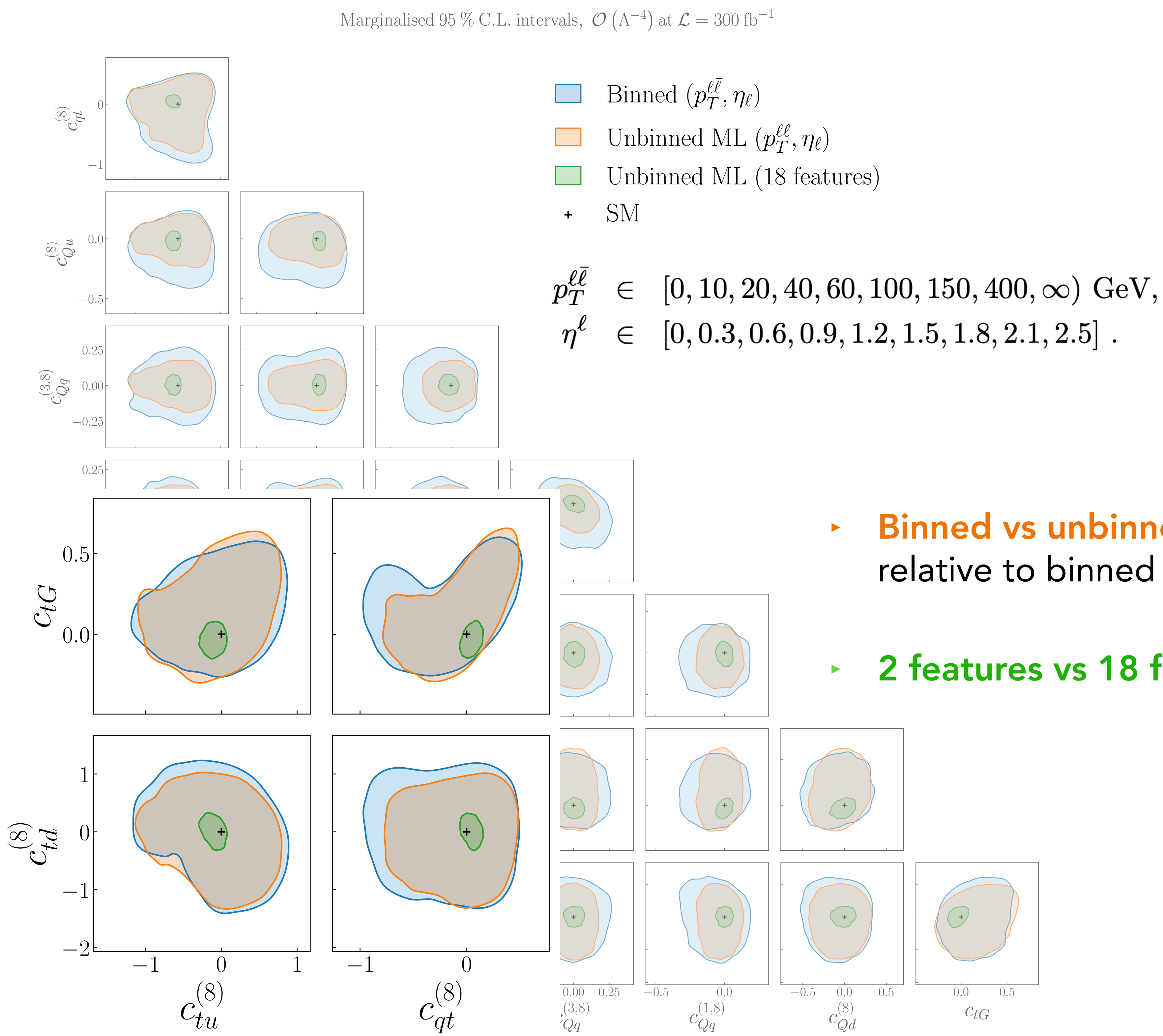
Process	N_{rep}	$\widetilde{N}_{\mathrm{ev}}$ (per replica)	N_{nn}	#trainings
$pp \to t\bar{t}$	50	10^5	4	200
$pp \to t\bar{t} \to b\bar{b}\ell^+\ell^-\nu_\ell\bar{\nu}_\ell$	25	10^5	40	1000

Let's go multivariate

- $pp \to t\bar{t} \to b\bar{b}\ell^+\ell^-\nu_\ell\bar{\nu}_\ell$: 18 features, 8 EFT coefficients
- $pp \to hZ \to b\bar{b}\ell^+\ell^-$: 7 features, 7 EFT coefficients

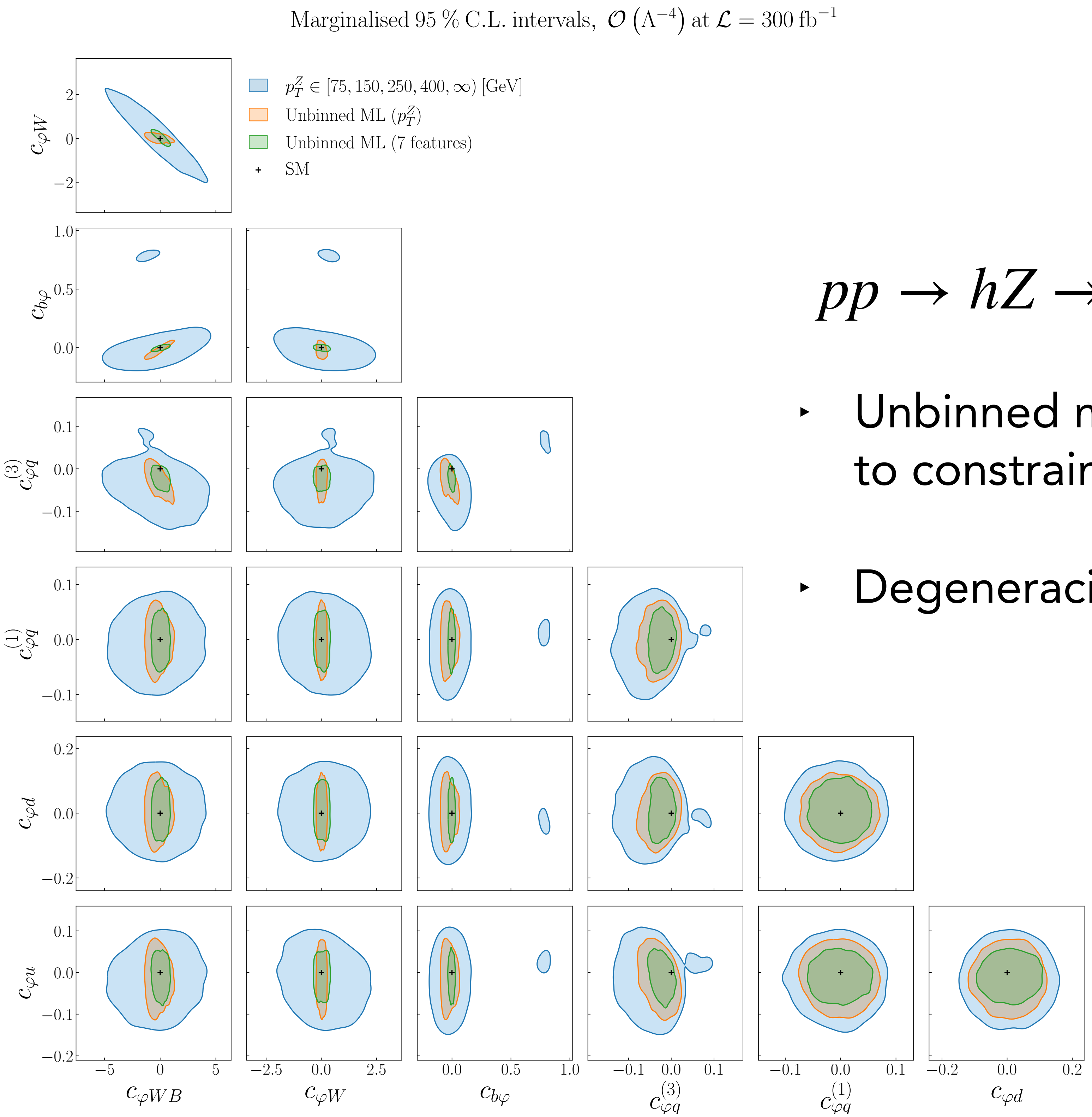


Unbinned observables in the top sector



- **Binned vs unbinned** in $(p_T^{\ell\bar{\ell}}, \eta_\ell)$ small improvement relative to binned setup
- **2 features vs 18 features:** big increase in sensitivity

Unbinned observables in Higgs + Z associated production

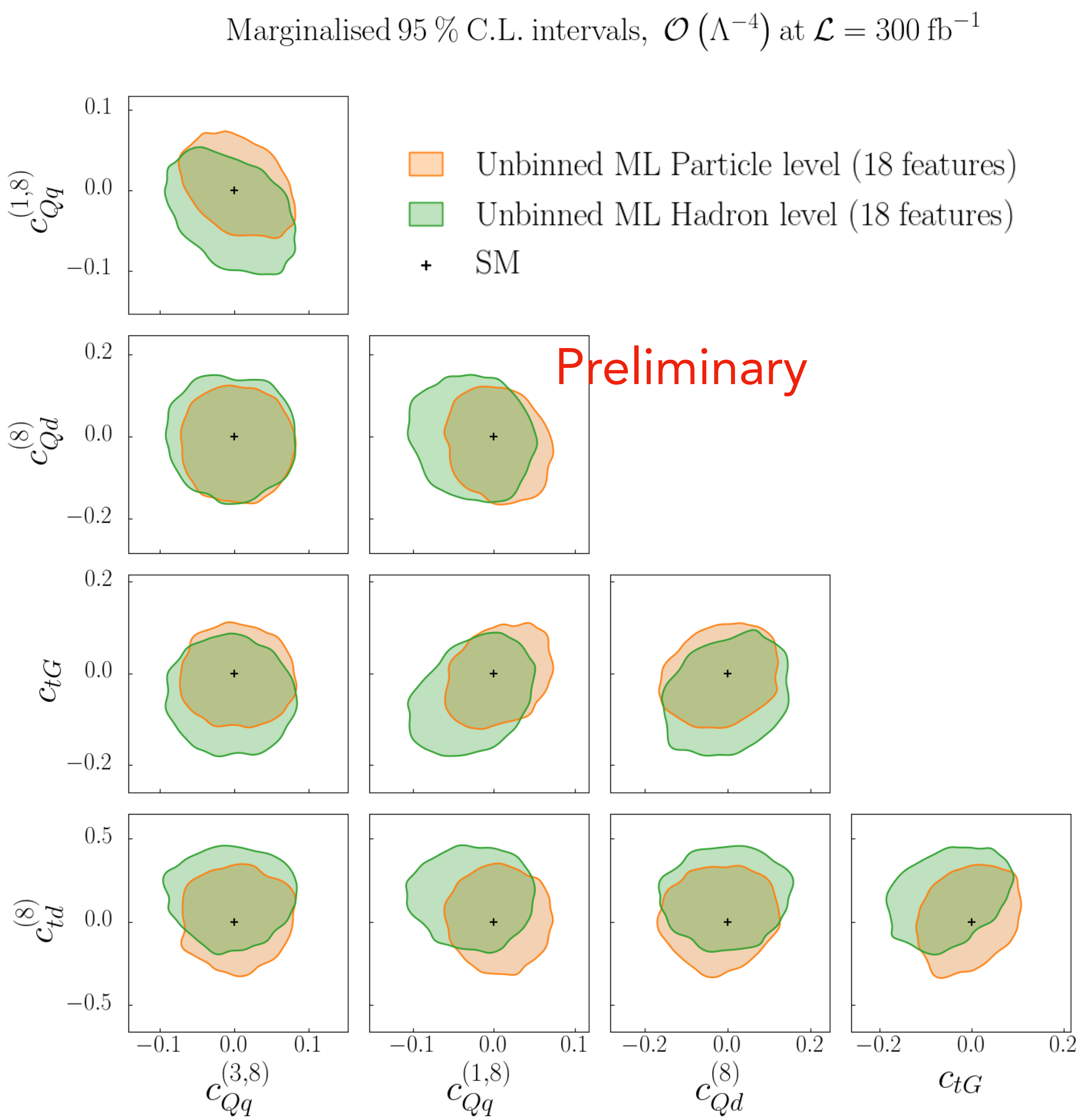


$$pp \to hZ \to b\bar{b}\ell^+\ell^-$$

- Unbinned multivariate data is advantageous to constrain the EFT parameter space
- Degeneracies get lifted

Ongoing efforts

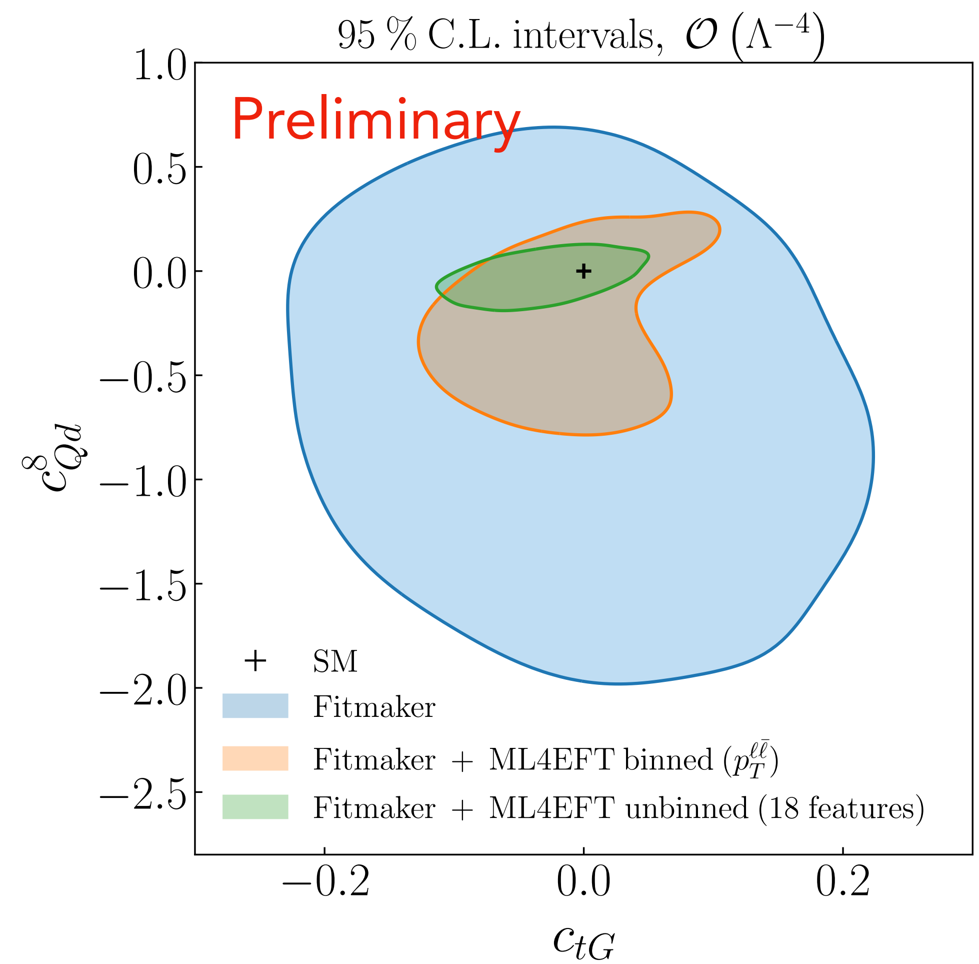
1. Hadronised level



MSc project by Pim Herbschleb

2. Integration into global fits

$$\log\mathcal{L}(c) = \sum_{k=1}^{N_D^{(\text{unbinned})}} \log\mathcal{L}_k^{\text{unbinned}}(c) + \sum_{k=1}^{N_D^{(\text{binned})}} \log\mathcal{L}_k^{\text{binned}}(c)$$



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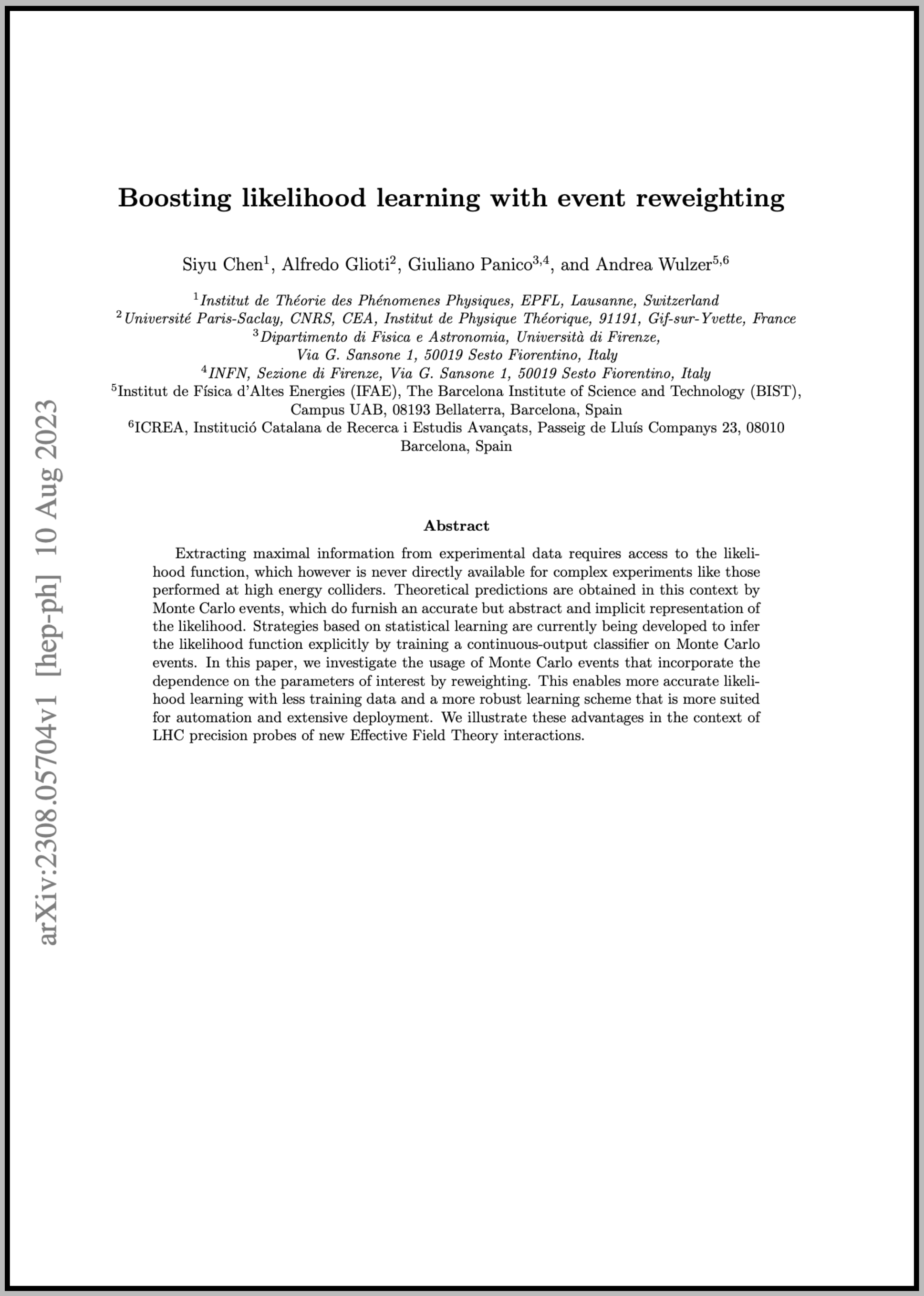

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