‘Profile Likelihoods on ML-Steroids’

Accelerating global SMEFT fits using neural importance sampling

Nikita Schmal

20/05/2025, IRN Terascale @ IPHC Strasbourg

Based on
[2411.00942] Theo Heimel, Tilman Plehn, Nikita Schmal

UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386

Global SMEFT Fits

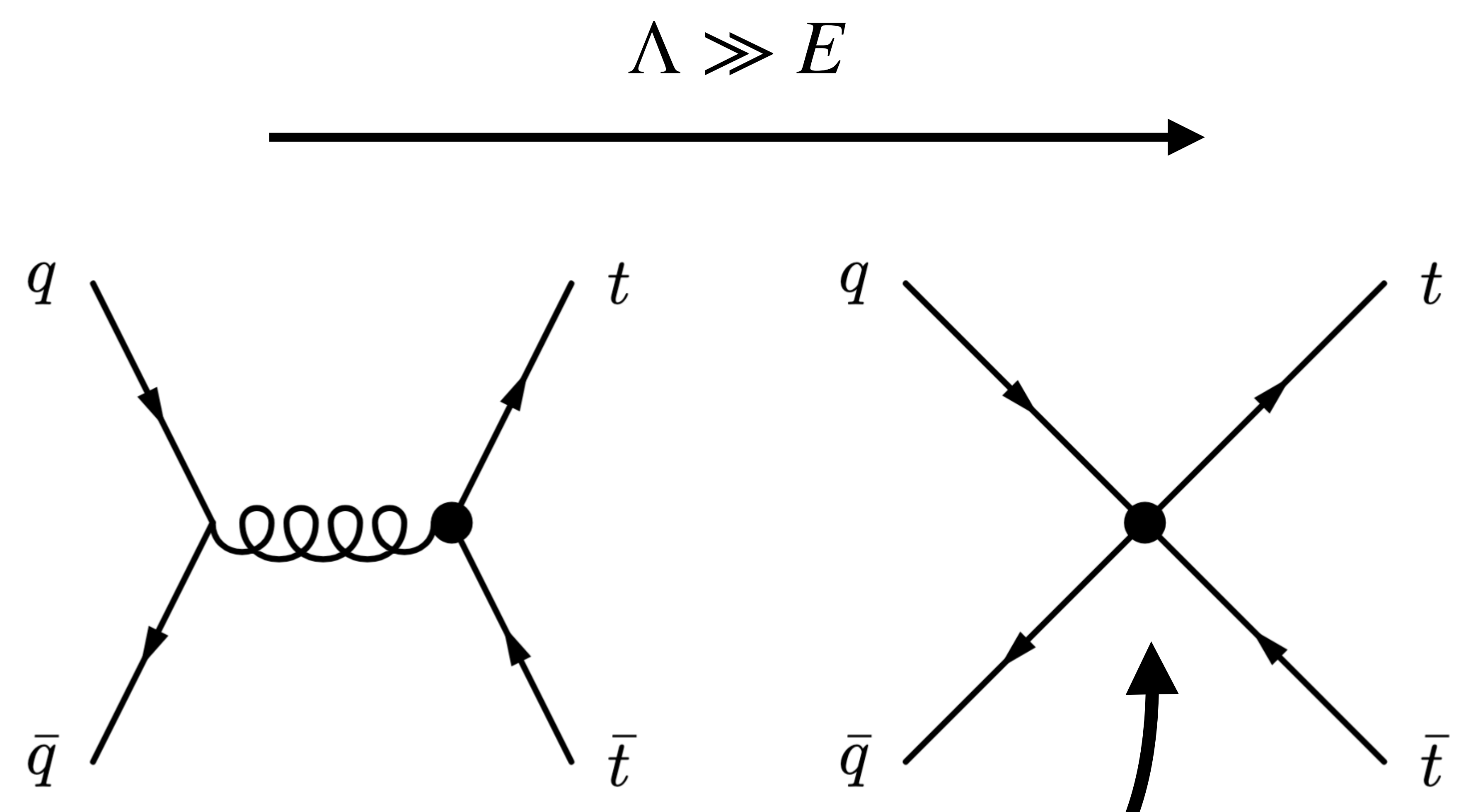
SMEFT predictions

- Model agnostic approach to look for signs of new physics

$$\mathscr{L}_{SMEFT} = \mathscr{L}_{SM} + \sum_i \frac{C_i}{\Lambda^2}\mathcal{O}_i^{(6)} + \dots$$

- Here: **Dimension 6** operators, up to quadratic contributions

Example: $t\bar{t}$ production



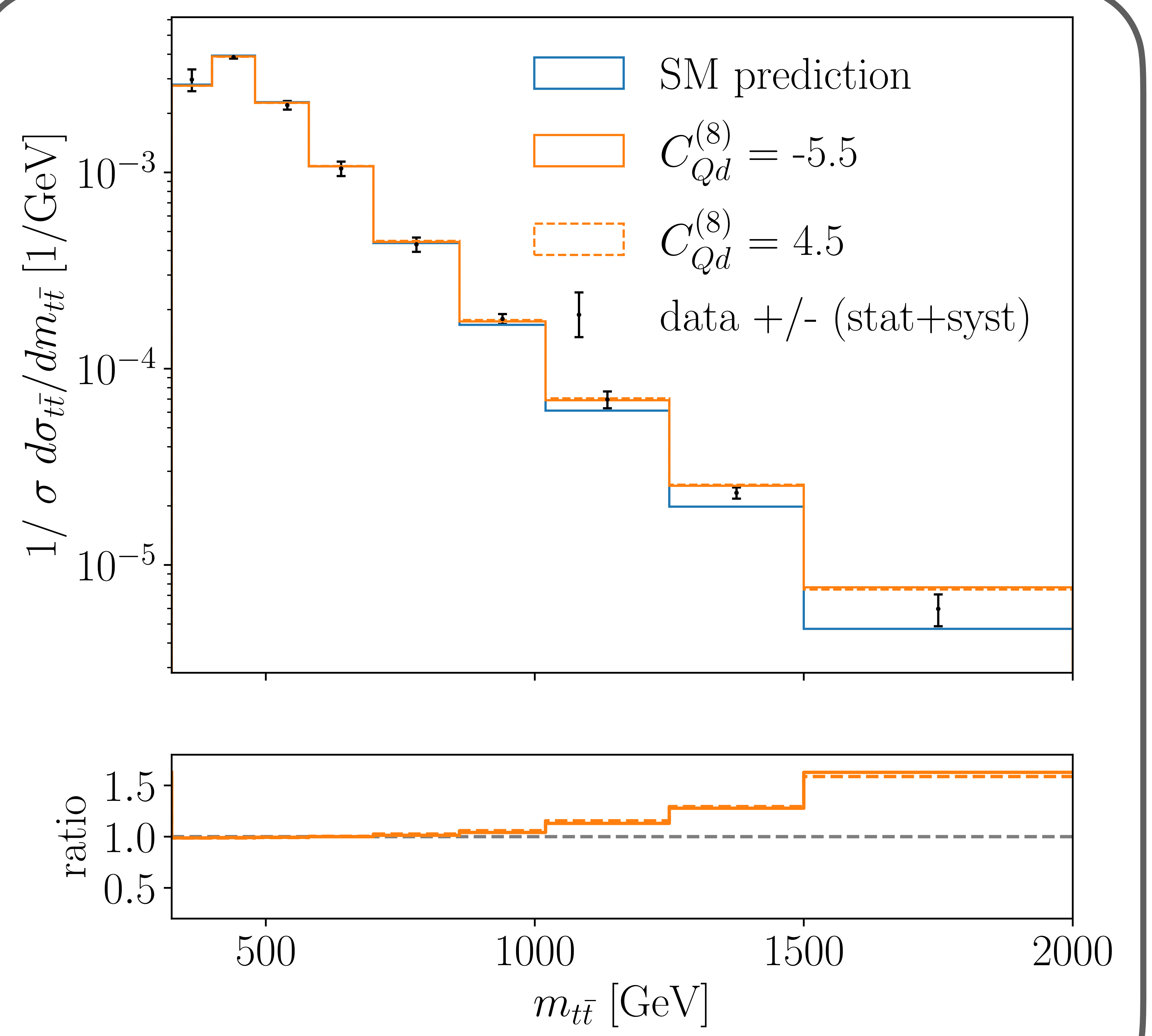
$$C_{Qd}^8 = (\bar{Q}\gamma_\mu T^A Q)(\bar{d}_i\gamma^\mu T^A d_i)$$

Global SMEFT Fits

SMEFT predictions

- Take data from experiment
- Simulation via e.g. MadGraph and SMEFTatNLO
- Predictions for each bin, given in **simple bilinear** form

$$p_i^{(b)} = W_{ijk} C_j^{(b)} \tilde{C}_k^{(b)} + B_i$$



[2312.12502], N. Elmer, M. Madigan, T. Plehn, N. Schmal

SFitter - Likelihood

Likelihood construction

$$L_{\text{excl}} = \text{Pois}(d \,|\, p(C, \underline{\theta, b}))\ \text{Pois}(b_{CR} \,|\, bk) \prod_i \underline{\mathscr{C}_i(\theta_i, \sigma_i)}$$

SMEFT contributions → C

Nuisance parameters → θ, b

Constraint terms → $\mathscr{C}_i(\theta_i, \sigma_i)$

Constraints

$\mathscr{C}_i(\theta_i, \sigma_i)$ →

- Systematic: **fully correlated** Gaussian
- Statistical: uncorrelated Gaussian
- Theory: $F(x \,|\, \sigma, \mu) = \dfrac{1}{2\sigma} \Theta\left[x - (\mu - \sigma)\right] \Theta\left[(\mu + \sigma) - x\right]$

SFitter - Profiling

Likelihood profiling

- Remove nuisances via **profiling** $L_{\text{prof}}(x) = \max_{\theta,b} L_{\text{excl}}$

Gaussian contribution

$$\log\, L_{\text{Gauss}}(\tilde{s}\,|\,d, b_{CR}) = \frac{(d - b_{CR} - \tilde{s}_\sigma)^2}{\sum_{\text{syst}} (\sigma_{d,i} - \sigma_{b,i})^2}$$

Poisson contribution

$$\log\, L_{\text{pois},b}(\tilde{s}\,|\,d, b_{CR}) = b_{CR} - (d - \tilde{s}_\sigma)\log(d - \tilde{s}_\sigma) + \log \frac{(d - \tilde{s}_\sigma)!}{b_{CR}!}$$

$$\log\, L_{\text{pois},d}(\tilde{s}\,|\,d, b_{CR}) = d - (\tilde{s}_\sigma + b_{CR})\log(\tilde{s}_\sigma + b_{CR}) + \log \frac{(\tilde{s}_\sigma + b_{CR})!}{d!}$$

Full likelihood

$$\frac{1}{L_{\text{full}}} \approx \frac{1}{L_{\text{Gauss}}} + \frac{1}{L_{\text{Poiss},b}} + \frac{1}{L_{\text{Poiss},d}}$$

GLOBAL SMEFT FITS

Going global

- Various processes constrain numerous different operators
- **Complementarity** of processes helps resolve blind directions

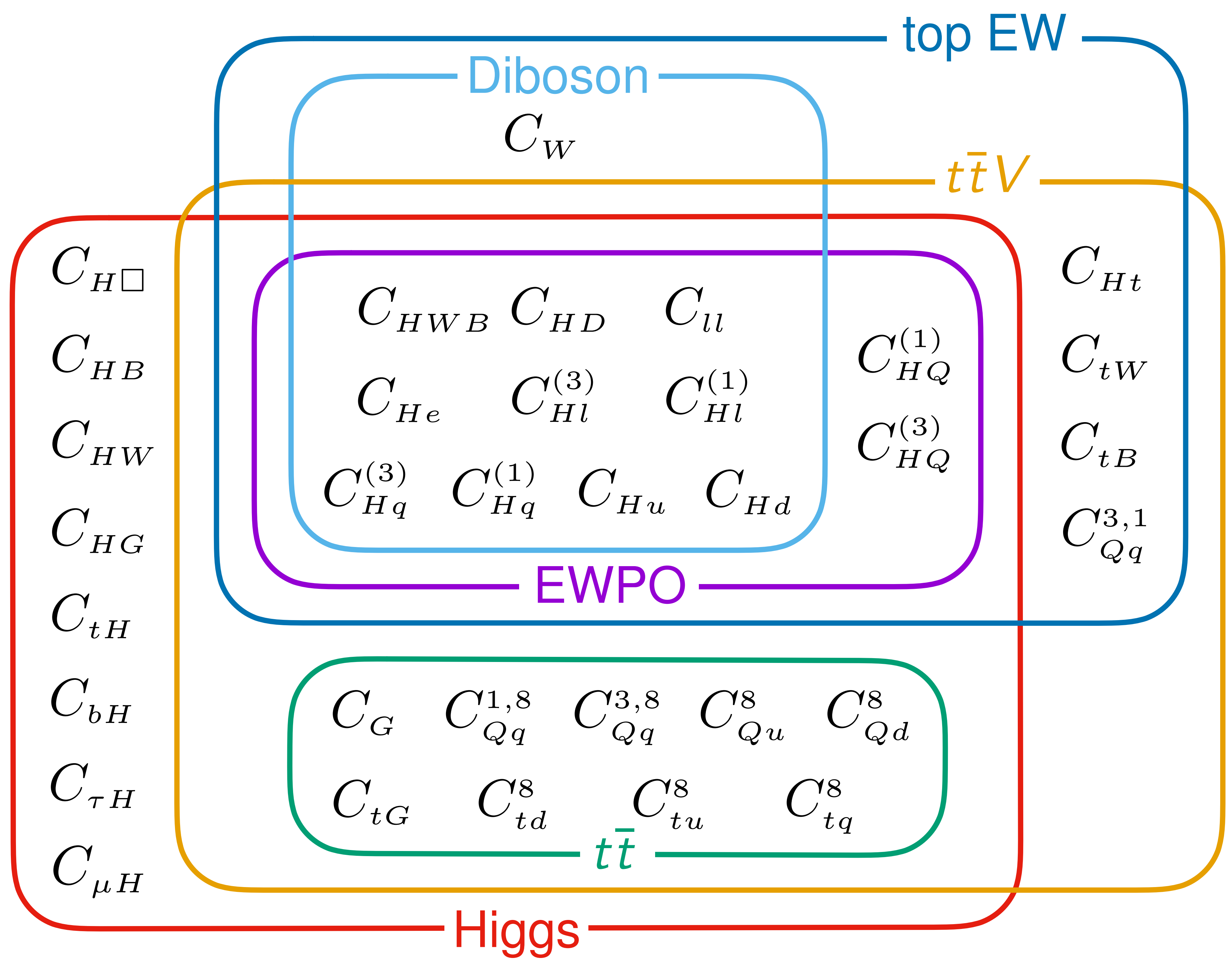
Wilson coeff		$t\bar{t}$	single t	tW	tZ	t-decay	$t\bar{t}Z$	$t\bar{t}W$
$C_{Qq}^{1,8}$		Λ^{-2}	–	–	–	–	Λ^{-2}	Λ^{-2}
$C_{Qq}^{3,8}$		Λ^{-2}	$\Lambda^{-4}\,[\Lambda^{-2}]$	–	$\Lambda^{-4}\,[\Lambda^{-2}]$	$\Lambda^{-4}\,[\Lambda^{-2}]$	Λ^{-2}	Λ^{-2}
C_{tu}^{8}, C_{td}^{8}	Eq.(3)	Λ^{-2}	–	–	–	–	Λ^{-2}	–
$C_{Qq}^{1,1}$		$\Lambda^{-4}\,[\Lambda^{-2}]$	–	–	–	–	$\Lambda^{-4}\,[\Lambda^{-2}]$	$\Lambda^{-4}\,[\Lambda^{-2}]$
$C_{Qq}^{3,1}$		$\Lambda^{-4}\,[\Lambda^{-2}]$	Λ^{-2}	–	Λ^{-2}	Λ^{-2}	$\Lambda^{-4}\,[\Lambda^{-2}]$	$\Lambda^{-4}\,[\Lambda^{-2}]$
C_{tu}^{1}, C_{td}^{1}		$\Lambda^{-4}\,[\Lambda^{-2}]$	–	–	–	–	$\Lambda^{-4}\,[\Lambda^{-2}]$	–
C_{Qu}^{8}, C_{Qd}^{8}		Λ^{-2}	–	–	–	–	Λ^{-2}	–
C_{tq}^{8}	Eq.(4)	Λ^{-2}	–	–	–	–	Λ^{-2}	Λ^{-2}
C_{Qu}^{1}, C_{Qd}^{1}		$\Lambda^{-4}\,[\Lambda^{-2}]$	–	–	–	–	$\Lambda^{-4}\,[\Lambda^{-2}]$	–
C_{tq}^{1}		$\Lambda^{-4}\,[\Lambda^{-2}]$	–	–	–	–	$\Lambda^{-4}\,[\Lambda^{-2}]$	$\Lambda^{-4}\,[\Lambda^{-2}]$
$C_{\phi Q}^{-}$		–	–	–	Λ^{-2}	–	Λ^{-2}	–
$C_{\phi Q}^{3}$		–	Λ^{-2}	Λ^{-2}	Λ^{-2}	Λ^{-2}	Λ^{-2}	–
$C_{\phi t}$		–	–	–	Λ^{-2}	–	Λ^{-2}	–
$C_{\phi tb}$	Eq.(5)	–	Λ^{-4}	Λ^{-4}	Λ^{-4}	Λ^{-4}	–	–
C_{tZ}		–	–	–	Λ^{-2}	–	Λ^{-2}	–
C_{tW}		–	Λ^{-2}	Λ^{-2}	Λ^{-2}	Λ^{-2}	–	–
C_{bW}		–	Λ^{-4}	Λ^{-4}	Λ^{-4}	Λ^{-4}	–	–
C_{tG}		Λ^{-2}	$[\Lambda^{-2}]$	Λ^{-2}	–	$[\Lambda^{-2}]$	Λ^{-2}	Λ^{-2}

[2312.12502], N. Elmer, M. Madigan, T. Plehn, N. Schmal

Global SMEFT Fits

Going global

- Various processes constrain numerous different operators
- **Complementarity** of processes helps resolve blind directions
- Necessary to study **cross-talk** between different physics sectors



[2012.02779], J. Ellis, M. Madigan, K. Mimasu, V. Sanz, T. You

SFitter - Dataset

Top sector

- Consider **Top** sector with **22 Wilson coefficients** [2312.12502]
  - 122 datapoints
  - many distributions (including boosted top)
  - includes $t\bar{t}$, $t\bar{t}Z$, $t\bar{t}W$ and SingleTop
  - also top decays, charge asymmetries

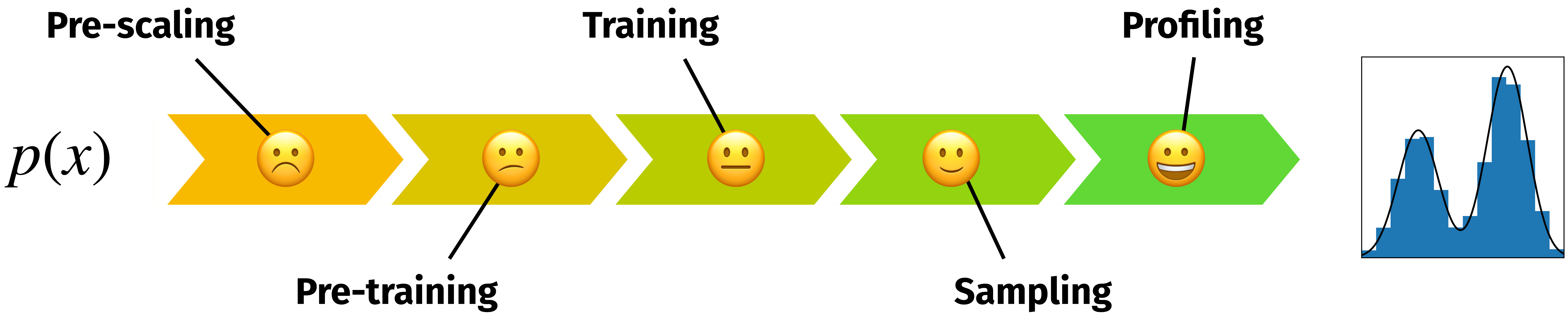
Higgs sector

- **Higgs** sector with **20 Wilson coefficients** [2208.08454]
  - 311 Higgs datapoints
  - 43 Di-Boson datapoints
  - 14 EWPOs (linear SMEFT contr.)
  - 4 high kinematic measurements

The five steps to happiness

Learning the likelihood

- How to extract constraints on the WCs?
- SFITTER makes use of MCMC, but that is too **slow**
- **Alternative:** Train a **normalizing flow** to speed this up



Pre-scaling

- Use annealed importance sampling (AIS) [Neal, 2001]
- $\log p_t(x) = (1 - \beta_t) \log p_0(x) + \beta_t \log p_T(x) \quad \text{with} \quad \beta_t = \frac{t}{T} \quad \text{and} \quad t = 1, \ldots, T$

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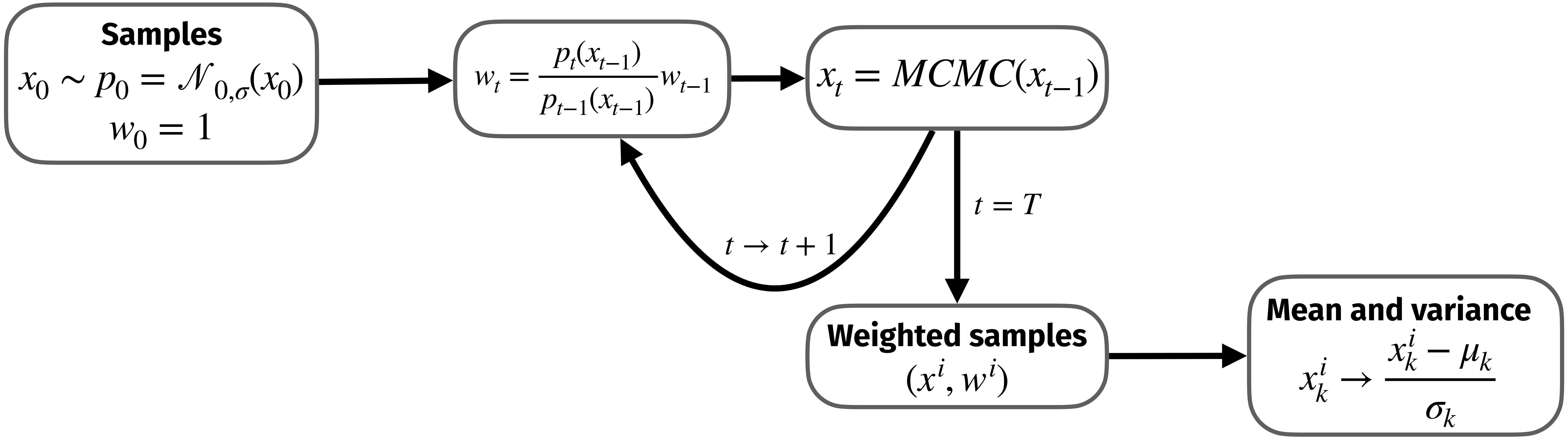


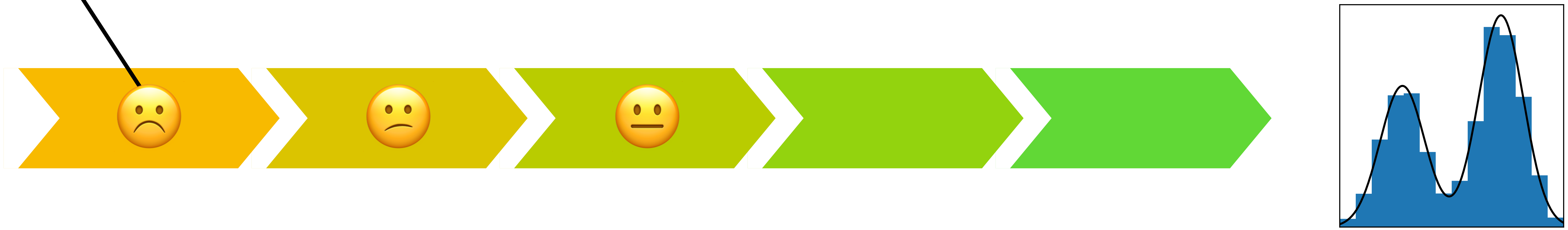
- **Re-scaled** parameters: Zero mean, unit variance

The five steps to happiness

Pre-scaling

- run many parallel MCs to determine mean, std.
- normalize distribution

$p(x)$



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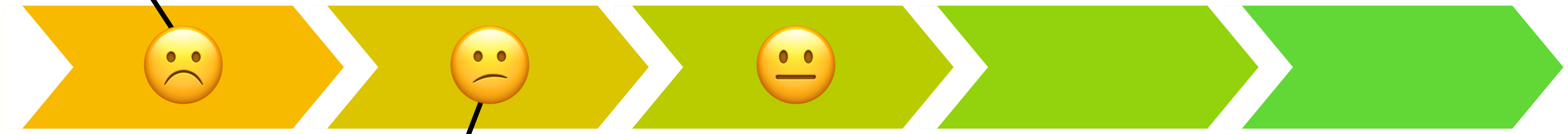
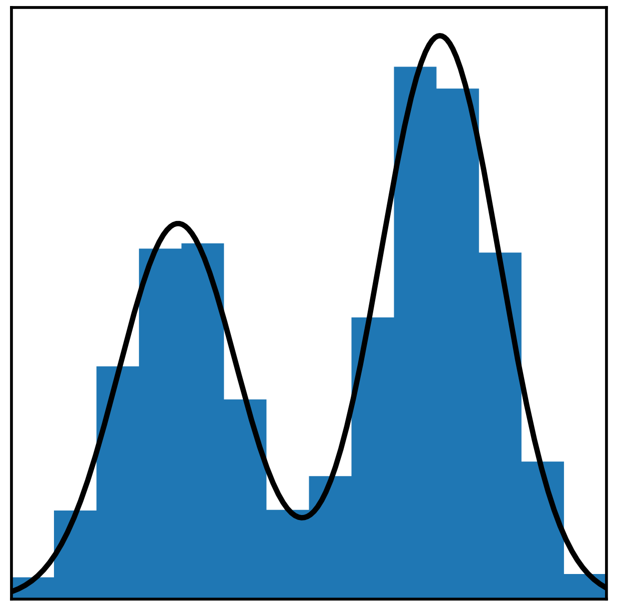




Pre-training

- use samples from pre-scaling to train network for a few steps
- better starting point for main training

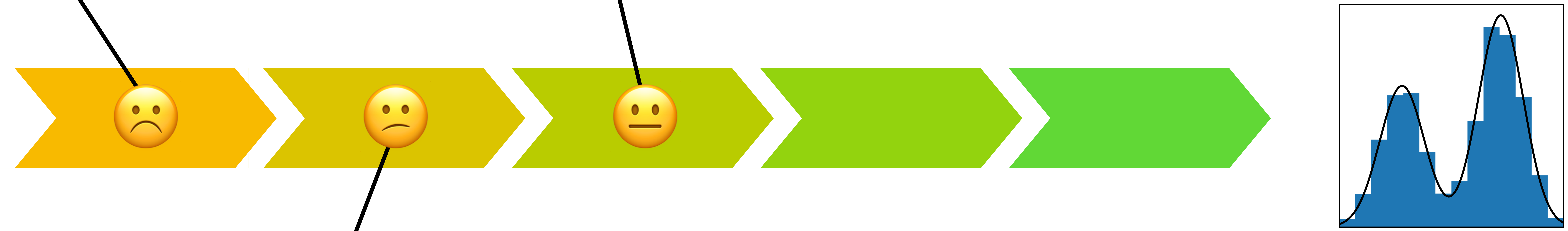
The five steps to happiness

Pre-scaling

- run many parallel MCs to determine mean, std.
- normalize distribution

Training

$p(x)$



Pre-training

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Training

- **Combine** the advantages of AIS with our flow [Midgley et al. 2208.01893]

Variance loss

$$L = \left\langle \frac{p(x)^2}{g_\theta(x)q(x)} \right\rangle_{x \sim q(x)}$$

Training

- **Combine** the advantages of AIS with our flow

[Midgley et al. 2208.01893]

Variance loss

$$L = \left\langle \frac{p(x)^2}{g_\theta(x)q(x)} \right\rangle_{x\sim q(x)}$$

Optimal proposal

$$q(x) = f_\theta(x) \equiv \frac{p(x)^2}{g_\theta(x)}$$

Training

- **Combine** the advantages of AIS with our flow [Midgley et al. 2208.01893]

Optimal proposal

$$q(x) = f_\theta(x) \equiv \frac{p(x)^2}{g_\theta(x)}$$

Intractable!

Variance loss

$$L = \left\langle \frac{p(x)^2}{g_\theta(x) q(x)} \right\rangle_{x \sim q(x)}$$

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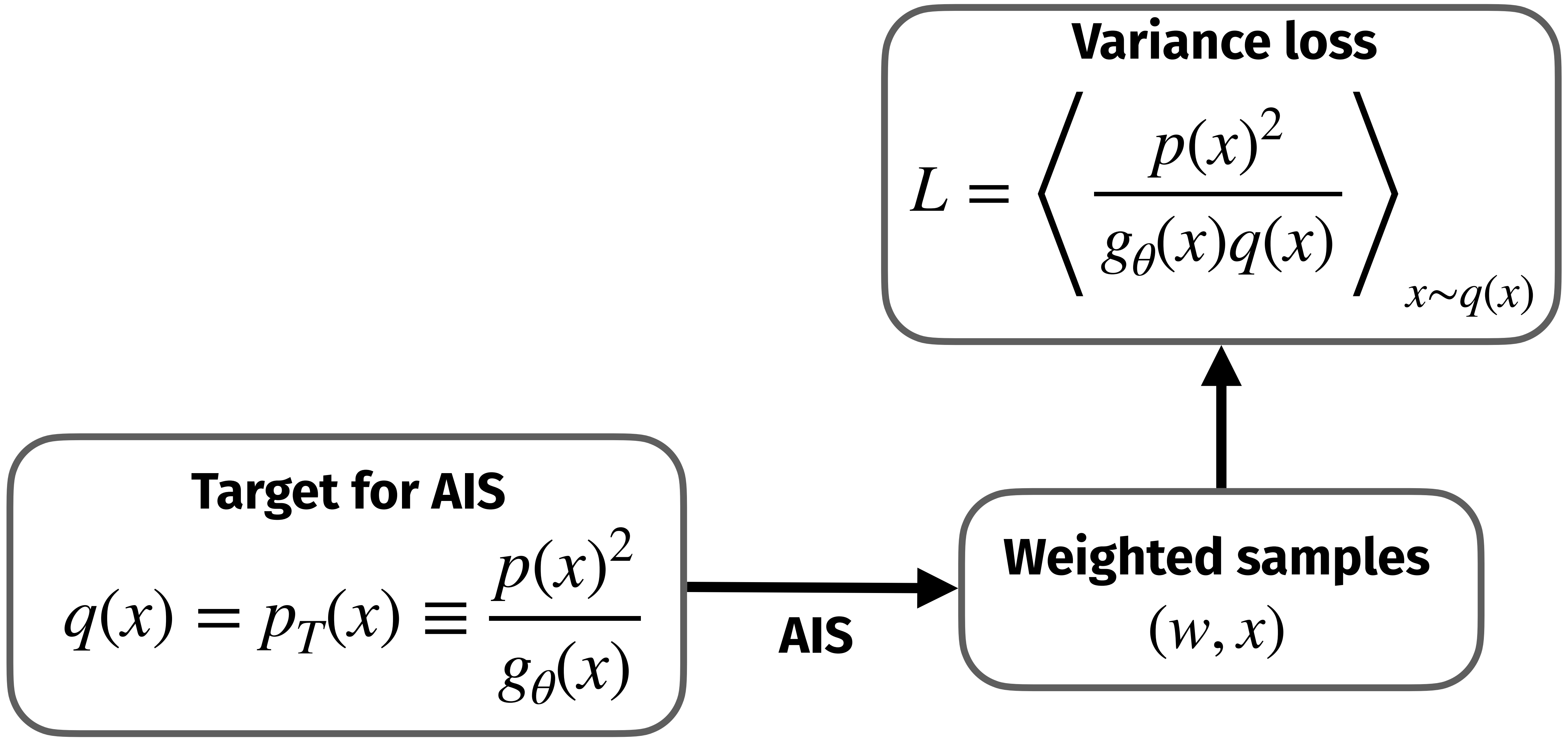

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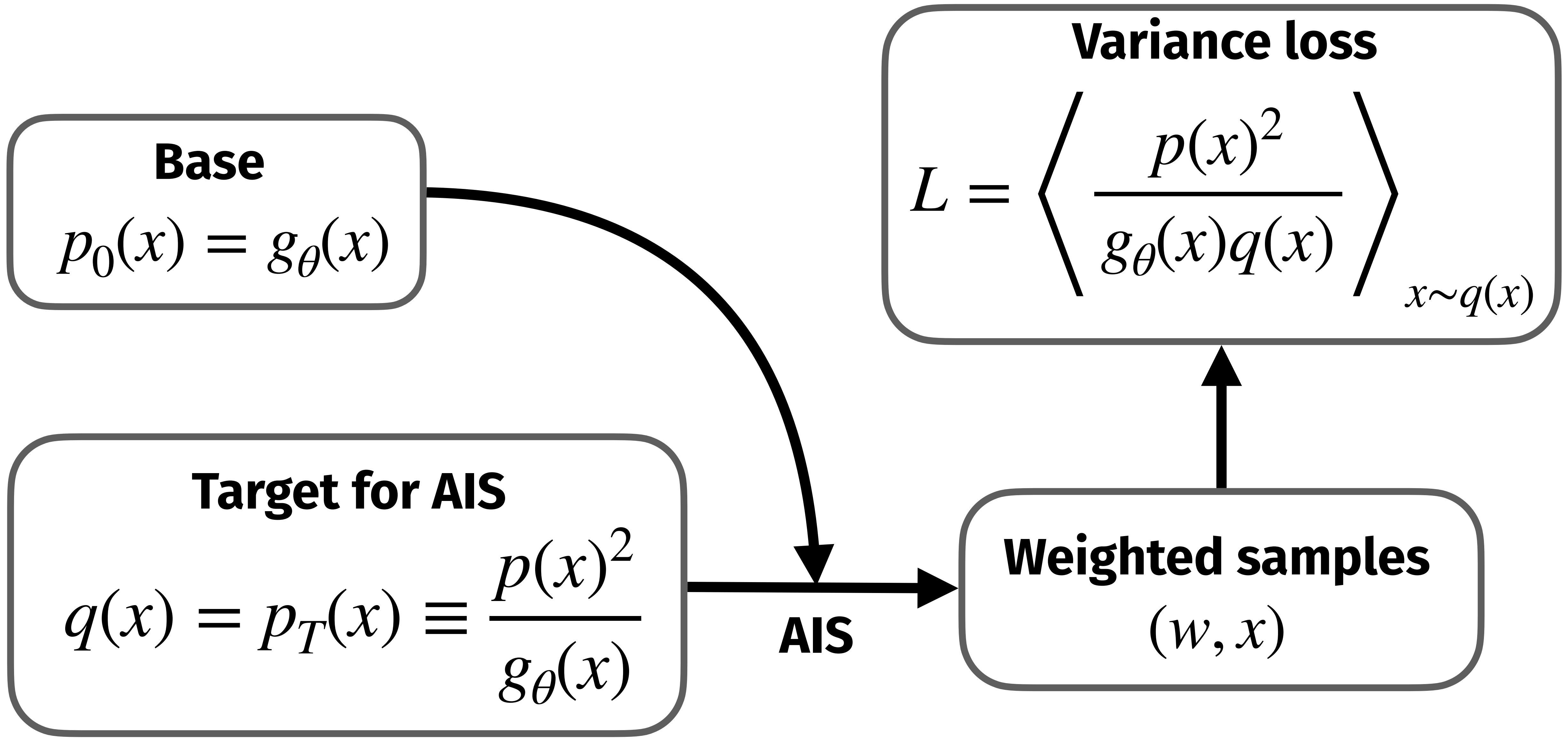

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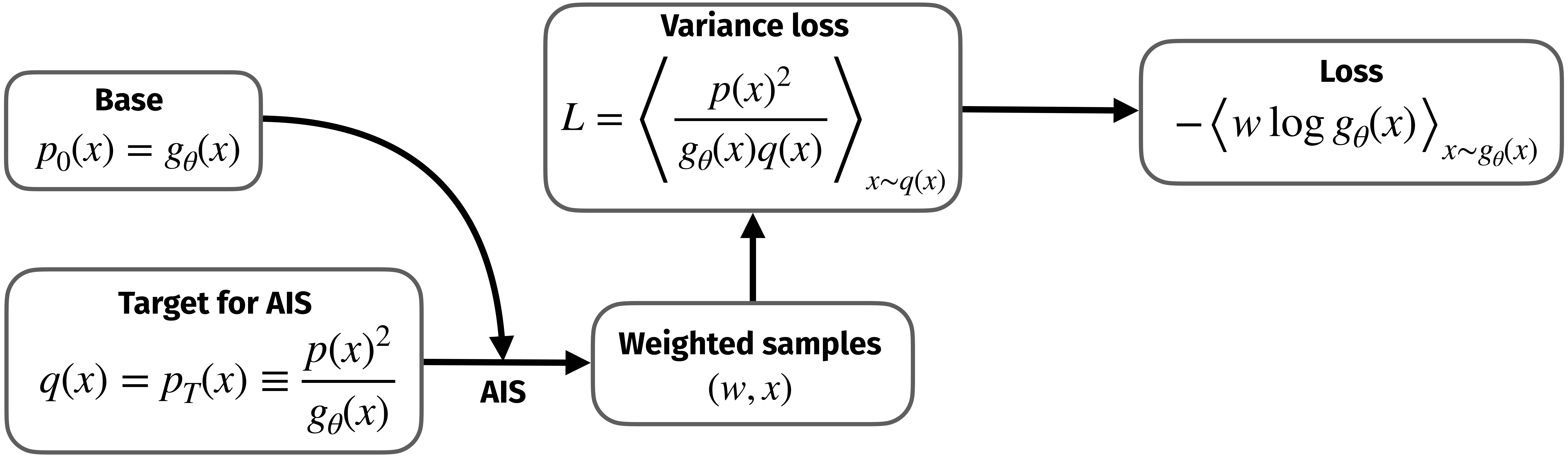
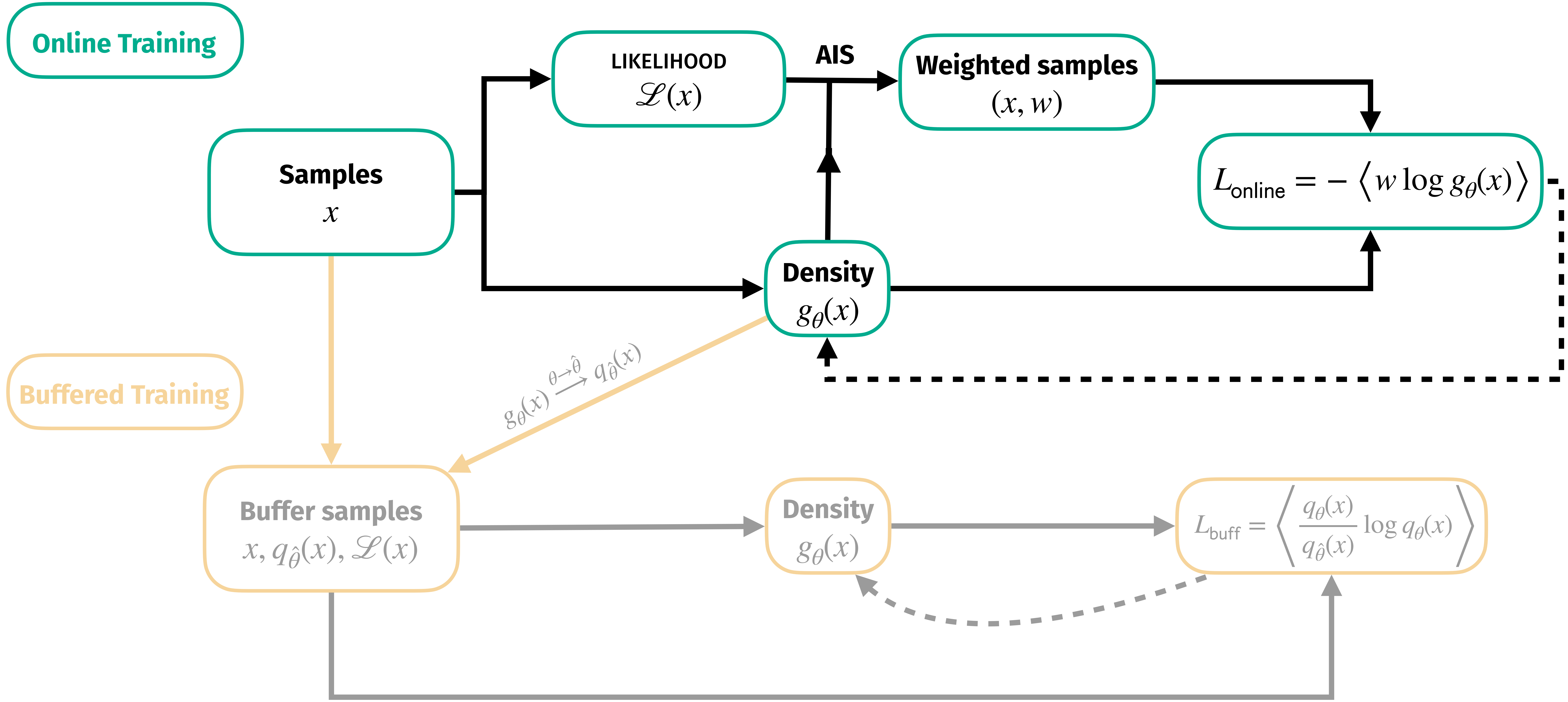


- Simple loss, **fast sampling** from $g_\theta(x)$.


Online Training
Samples
x
LIKELIHOOD
$\mathscr{L}(x)$
AIS
Weighted samples
(x, w)
$L_{\text{online}} = -\left\langle w \log g_\theta(x) \right\rangle$
Density
$g_\theta(x)$
$g_\theta(x) \xrightarrow{\theta \to \hat{\theta}} q_{\hat{\theta}}(x)$
Buffered Training
Buffer samples
$x, q_{\hat{\theta}}(x), \mathscr{L}(x)$
Density
$g_\theta(x)$
$L_{\text{buff}} = \left\langle \frac{q_\theta(x)}{q_{\hat{\theta}}(x)} \log q_\theta(x) \right\rangle$

To profile or to marginalize

How to compute constraints from high-dimensional likelihood?

Profiling

Look for the **maximum** in parameter space

$$\max_T p(M\,|\,T)$$

Marginalization

Integrate over parameter space

$$\int_T p(T\,|\,M) = \int_T p(M\,|\,T)\frac{p(T)}{p(M)}$$

→ Support **both** in our global fits

The final steps to happiness

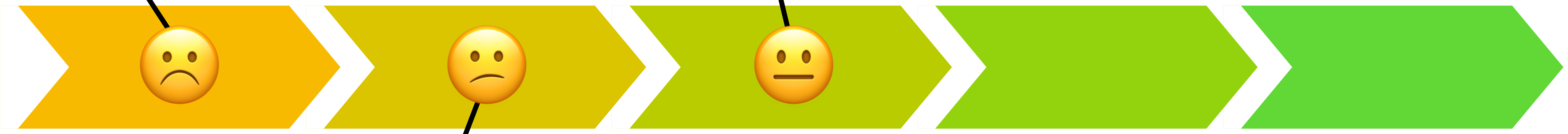
Pre-scaling

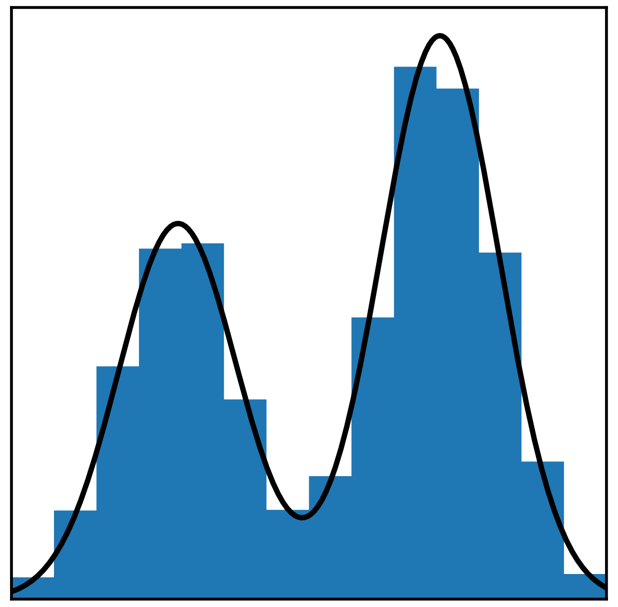
- run many parallel MCs to determine mean, std.
- normalize distribution

Training

- similar to MadNIS
- online + buffered training
- refine samples using small number of MCMC steps

$p(x)$





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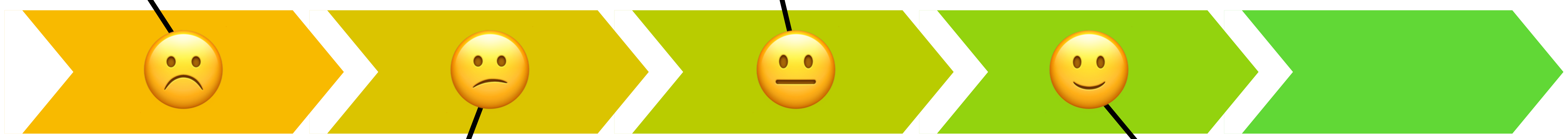

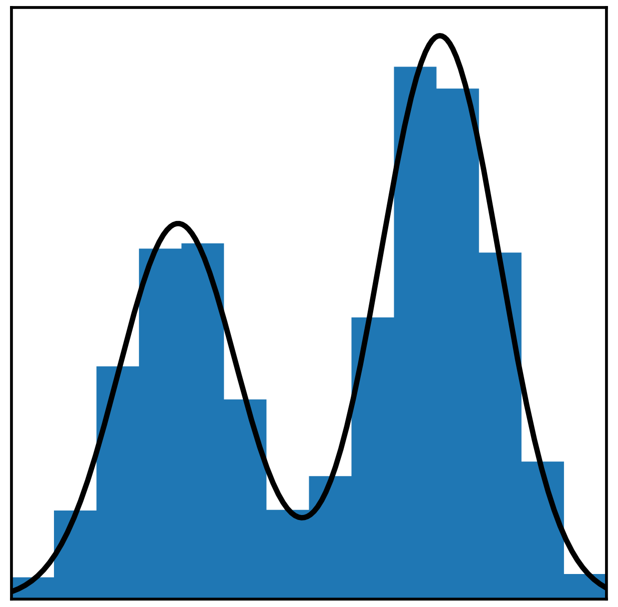

Pre-training

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Sampling

- generate weighted samples
- keep track of points with highest likelihood in each bin

The final steps to happiness

Pre-scaling

- run many parallel MCs to determine mean, std.
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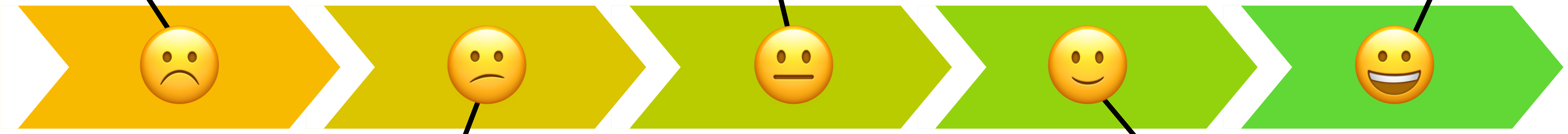
Training

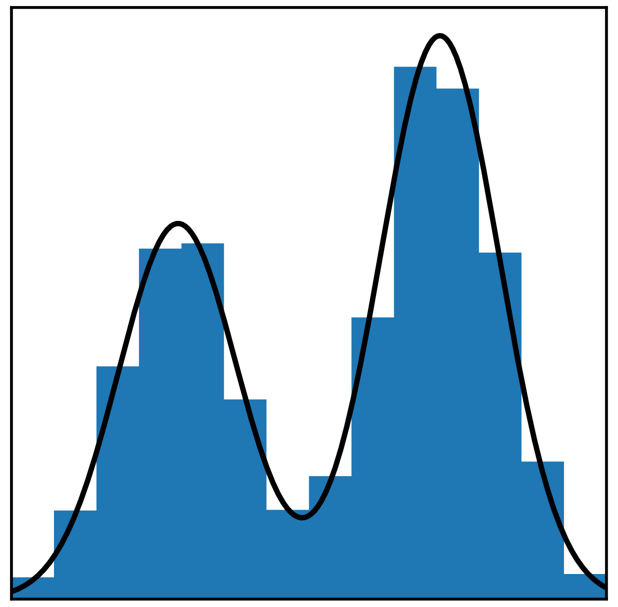
- similar to MadNIS
- online + buffered training
- refine samples using small number of MCMC steps

Profiling

- run maximization algorithm for each bin (L-BFGS)
- use gradient information

$p(x)$





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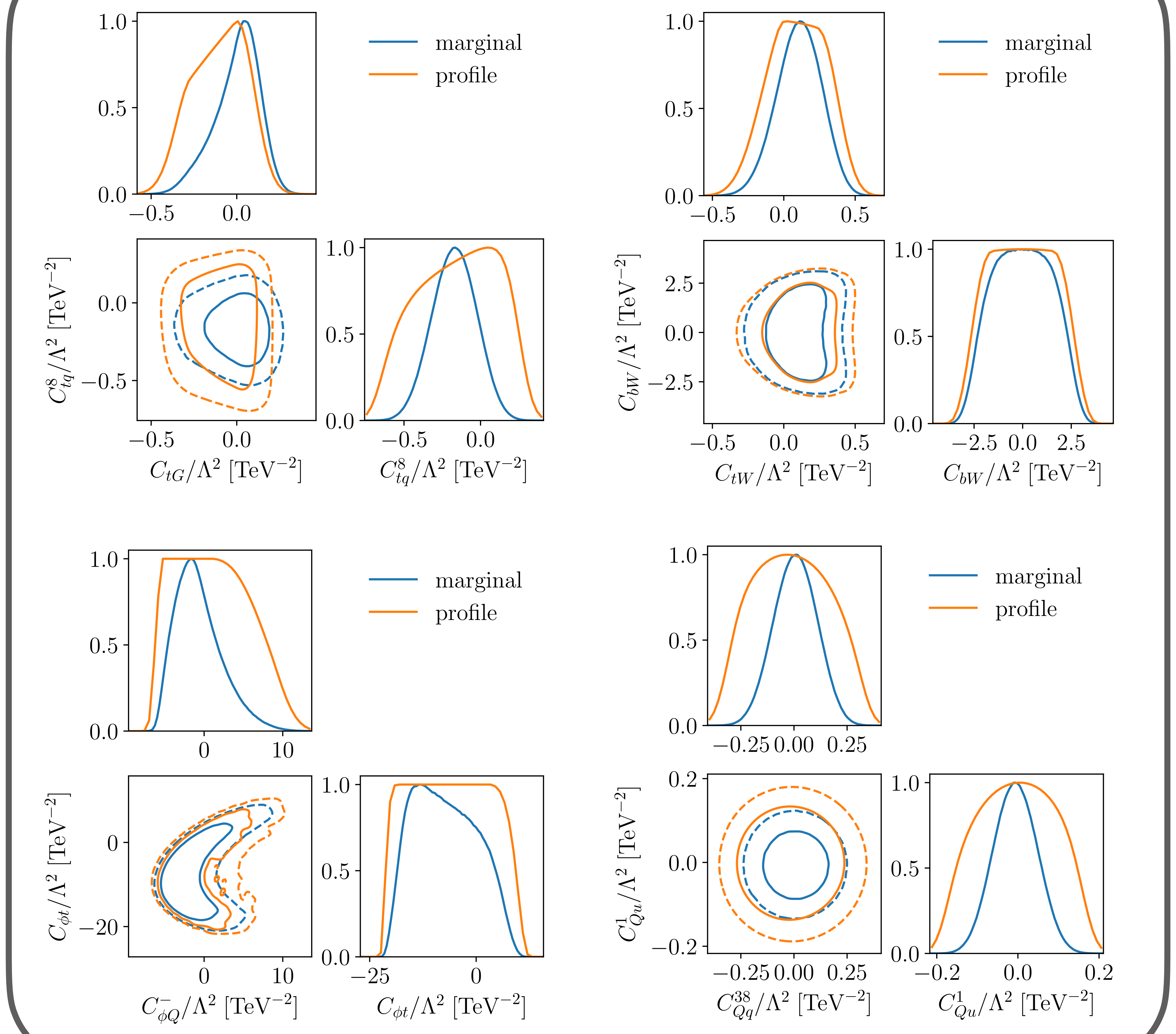
Results

Top likelihood

- Simple likelihood, mostly unfolded data
- Large effect from **theory uncertainties**
- **Smooth results** for both profiling and marginalization

[2411.00942]



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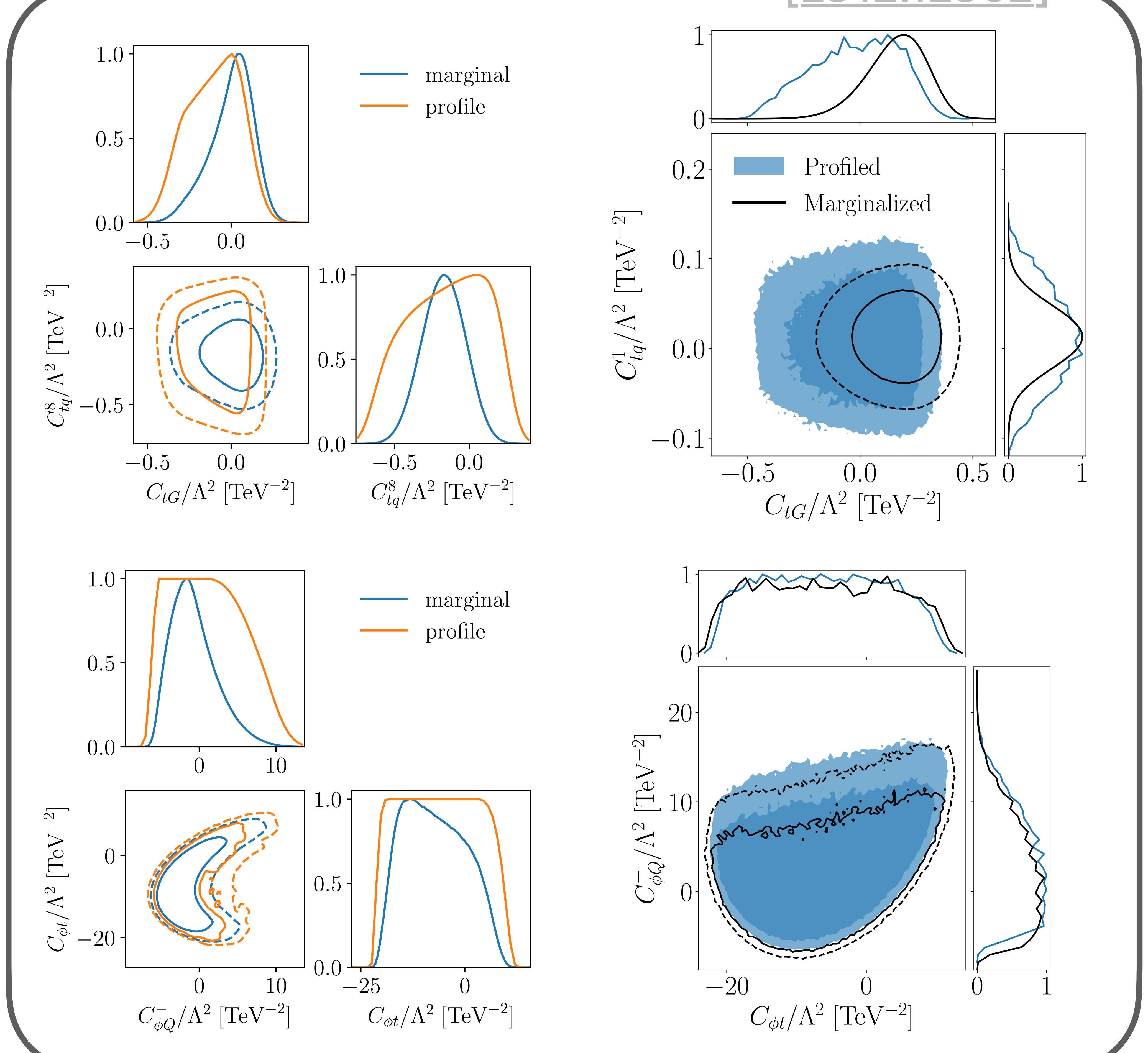


Performance

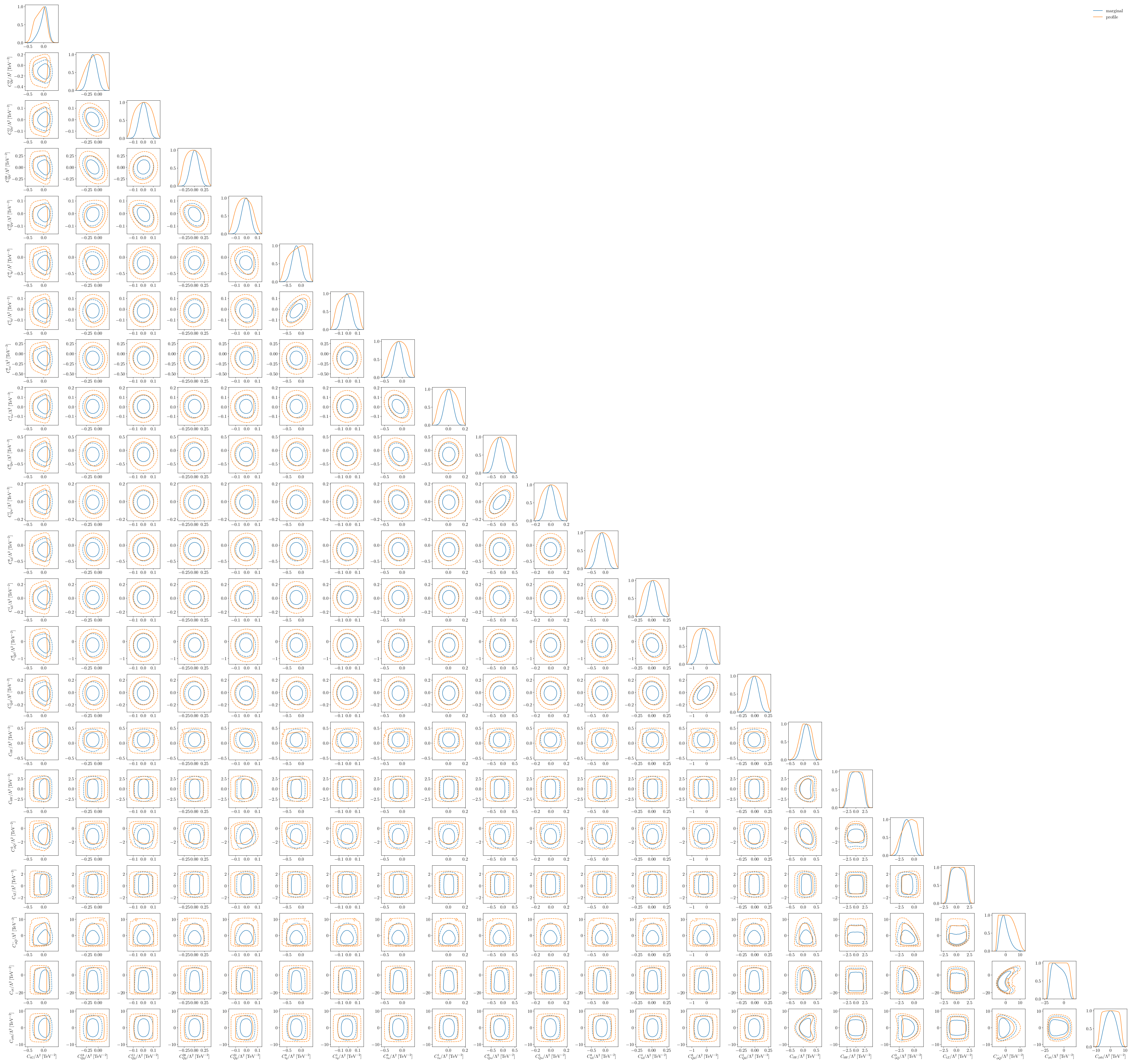
Top likelihood

- For simple likelihoods sampling on both CPU and GPU is fast
- Training + sampling done in around **a single minute**
- Most time spent on **profiling**

[2411.00942]

	Top	Higgs-gauge	Combined
Dimensions	22	20	42
Training batches	100	2000	6000
Samples	10M	200M	100M
Effective sample size	7.1M	97M	21M
Pre-scaling time	7s	3.5min	5.3min
Pre-training time	18s	1.7min	2.5min
Training time	36s	17.3min	1.2h
Sampling time	26s	14.8min	17.6min
Profiling time	17.7min	24.8min	3.7h
Number of CPUs	20	80	120
Accepted samples	37M	26.4M	60M
CPU sampling time	29min 49s	3h 23min	20h 50min
CPU profiling time	4min 43s	8min 24s	N/A

Performance



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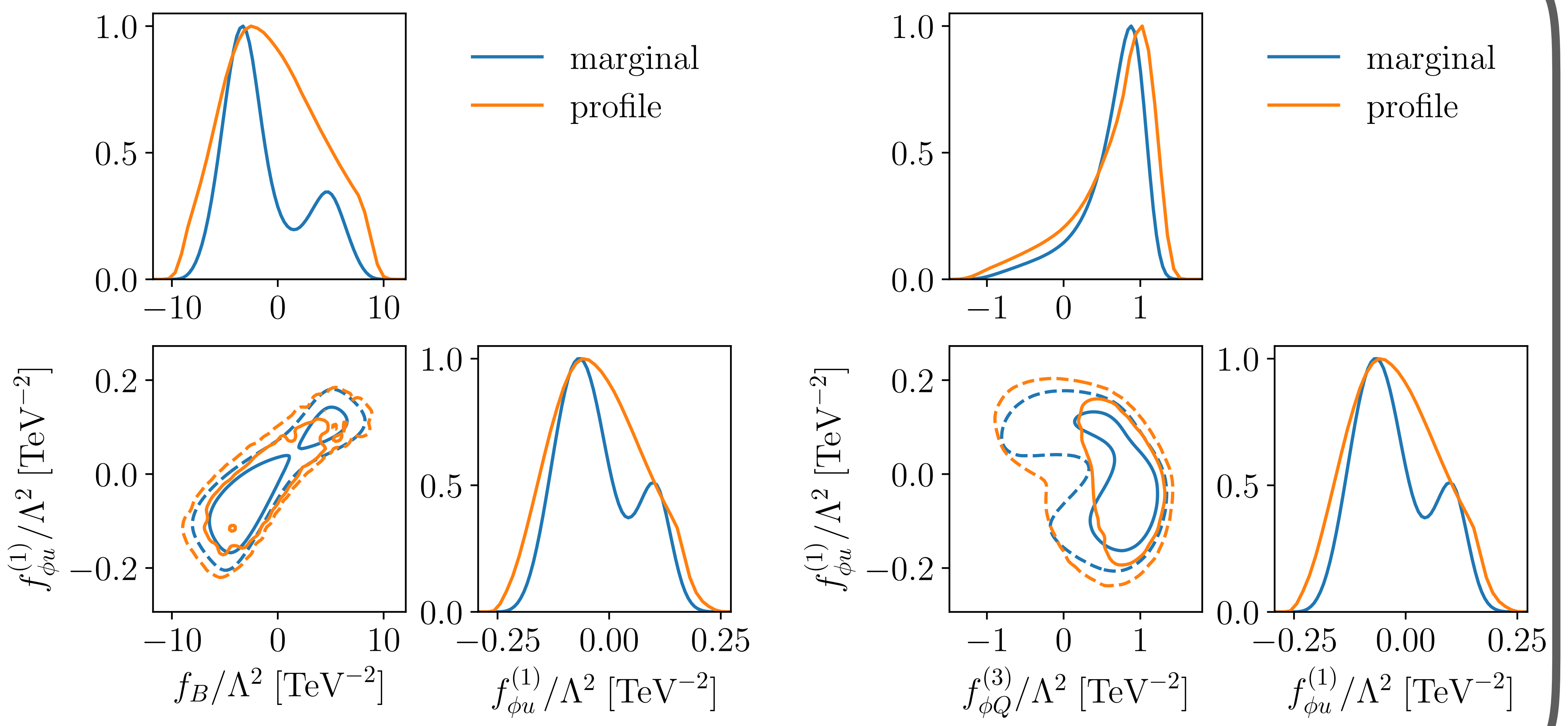
Results

Higgs likelihood

- More **complicated likelihood**
  - more measurements
  - less unfolded data
- Many coefficients with **multiple modes**
- Significantly **smoother results** for profiling

[2411.00942]



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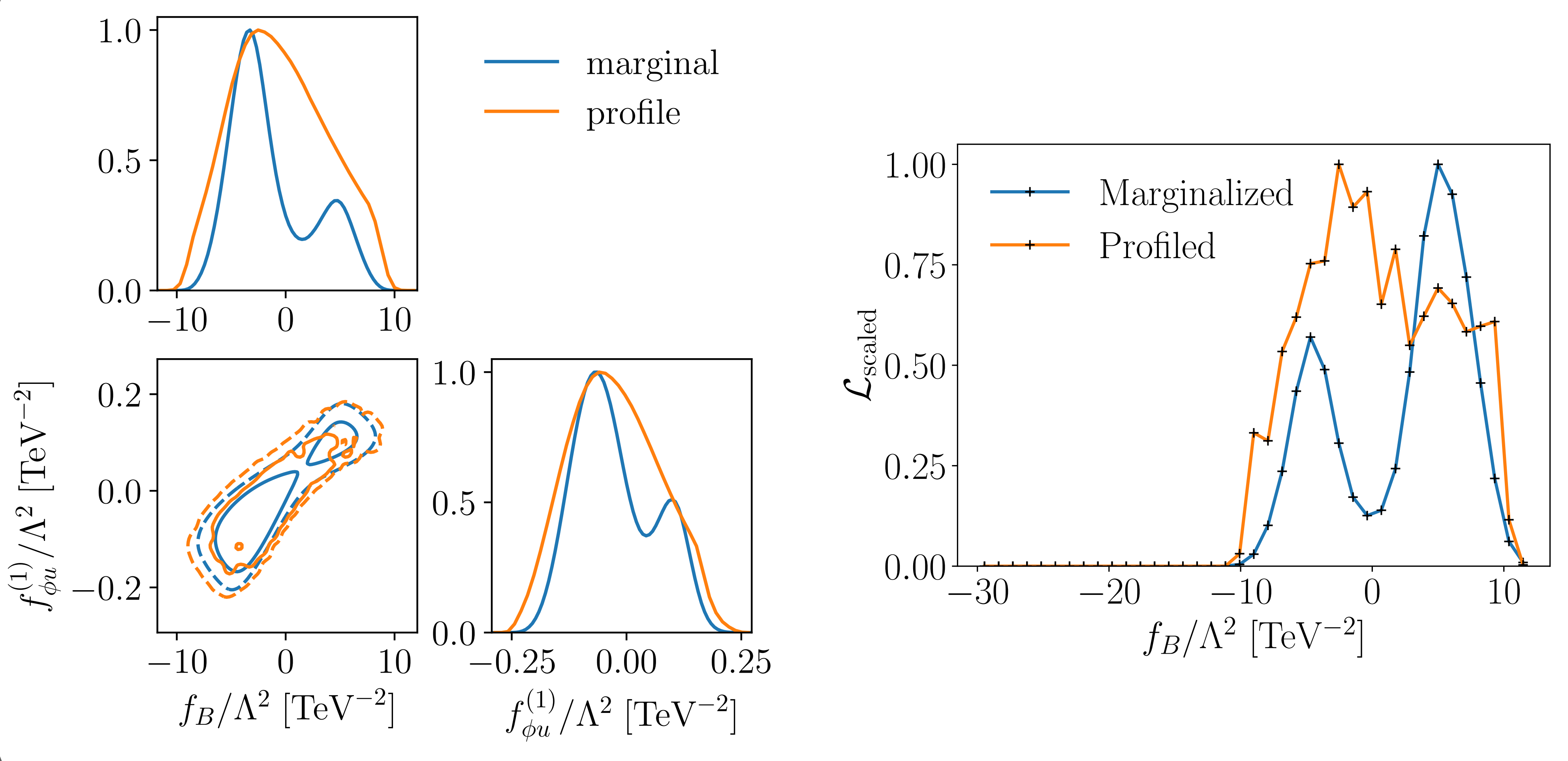
[2208.08454]



Performance

Higgs likelihood

- Already requires 4x CPUs for good results
- Slightly longer training, significantly faster even for complicated likelihoods

[2411.00942]

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Performance

Combined likelihood

- Full combined likelihood requires serious training
- Sampling **orders of magnitude** faster
- **Reliable profiled results**, previously out of reach for CPU implementation

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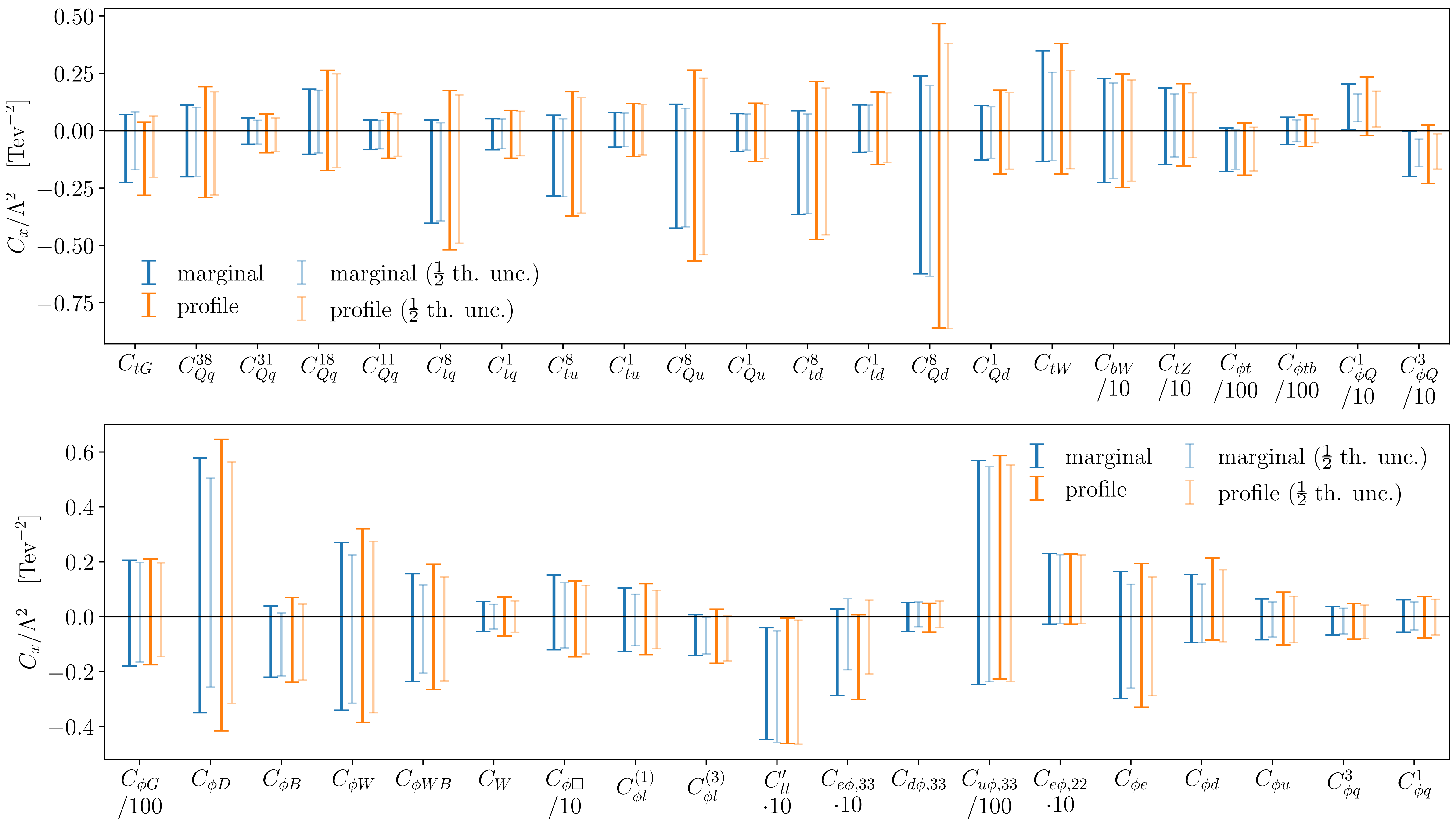
Final results



- Previously: Takes (at least) a day to compute these constraints
- **Now:** Can find signs for new physics **during lunch break** (+coffee)

Summary

Summary

- NIS: powerful tool to **accelerate sampling**
- Significantly **improves sampling speed** of complex likelihoods while simultaneously providing **smoother** results

Conclusion

- The five steps to happiness help fundamentally improve SFITTER studies
- Perfect time for further improvements

Appendix/Backup

Hyperparameters

		Top	Higgs-gauge	Combined
Architecture	Coupling blocks	RQ splines		
	Spline bins	16		
	Subnet layers	3		
	Hidden layers	64		
Pre-scaling	Number of samples	10240	40960	40960
	AIS steps	1500	5500	5500
	Target acceptance	0.33		
Pre-training	Batch size	1024		
	Epochs	15	6	6
	MCMC steps between batches	20	10	10
Training	Learning rate	0.001		
	Batch size	1024		
	Batches	100	2000	6000
	AIS steps	4	4	8
	Buffer capacity	262k		
	Ratio buffered/online steps	6		
Sampling	Batches	100	2000	1000
	Batch size	100k		
	Marginalization bins, 1D	80		
	Marginalization bins, 2D	40		
	Profiling bins, 1D	40		
	Profiling bins, 2D	30	30	20
Profiling	Batch size	100k		
	Optimizer	LBFGS		
	Optimization steps	200		

Top operator definitions

Operator	Definition	Operator	Definition
$\mathcal{O}_{Qq}^{1,8}$	$(\bar{Q}\gamma_\mu T^A Q)(\bar{q}_i\gamma^\mu T^A q_i)$	$\mathcal{O}_{tu}^{8}$	$(\bar{t}\gamma_\mu T^A t)(\bar{u}_i\gamma^\mu T^A u_i)$
$\mathcal{O}_{Qq}^{1,1}$	$(\bar{Q}\gamma_\mu Q)(\bar{q}_i\gamma^\mu q_i)$	$\mathcal{O}_{tu}^{1}$	$(\bar{t}\gamma_\mu t)(\bar{u}_i\gamma^\mu u_i)$
$\mathcal{O}_{Qq}^{3,8}$	$(\bar{Q}\gamma_\mu T^A\tau^I Q)(\bar{q}_i\gamma^\mu T^A\tau^I q_i)$	$\mathcal{O}_{td}^{8}$	$(\bar{t}\gamma^\mu T^A t)(\bar{d}_i\gamma_\mu T^A d_i)$
$\mathcal{O}_{Qq}^{3,1}$	$(\bar{Q}\gamma_\mu\tau^I Q)(\bar{q}_i\gamma^\mu\tau^I q_i)$	$\mathcal{O}_{td}^{1}$	$(\bar{t}\gamma^\mu t)(\bar{d}_i\gamma_\mu d_i)$
$\mathcal{O}_{Qu}^{8}$	$(\bar{Q}\gamma^\mu T^A Q)(\bar{u}_i\gamma_\mu T^A u_i)$	$\mathcal{O}_{Qd}^{1}$	$(\bar{Q}\gamma^\mu Q)(\bar{d}_i\gamma_\mu d_i)$
$\mathcal{O}_{Qu}^{1}$	$(\bar{Q}\gamma^\mu Q)(\bar{u}_i\gamma_\mu u_i)$	$\mathcal{O}_{tq}^{8}$	$(\bar{q}_i\gamma^\mu T^A q_i)(\bar{t}\gamma_\mu T^A t)$
$\mathcal{O}_{Qd}^{8}$	$(\bar{Q}\gamma^\mu T^A Q)(\bar{d}_i\gamma_\mu T^A d_i)$	$\mathcal{O}_{tq}^{1}$	$(\bar{q}_i\gamma^\mu q_i)(\bar{t}\gamma_\mu t)$
$\mathcal{O}_{\phi Q}^{1}$	$(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{Q}\gamma^\mu Q)$	$^\ddagger\mathcal{O}_{tB}$	$(\bar{Q}\sigma^{\mu\nu}t)\tilde{\phi}B_{\mu\nu}$
$\mathcal{O}_{\phi Q}^{3}$	$(\phi^\dagger i\overleftrightarrow{D}_\mu^I\phi)(\bar{Q}\gamma^\mu\tau^I Q)$	$^\ddagger\mathcal{O}_{tW}$	$(\bar{Q}\sigma^{\mu\nu}t)\tau^I\tilde{\phi}W_{\mu\nu}^I$
$\mathcal{O}_{\phi t}$	$(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{t}\gamma^\mu t)$	$^\ddagger\mathcal{O}_{bW}$	$(\bar{Q}\sigma^{\mu\nu}b)\tau^I\phi W_{\mu\nu}^I$
$^\ddagger\mathcal{O}_{\phi tb}$	$(\tilde{\phi}^\dagger iD_\mu\phi)(\bar{t}\gamma^\mu b)$	$^\ddagger\mathcal{O}_{tG}$	$(\bar{Q}\sigma^{\mu\nu}T^A t)\tilde{\phi}G_{\mu\nu}^A$

Higgs-gauge operator definitions (HISZ)

Operator	Definition	Operator	Definition
$\mathcal{O}_{GG}$	$\phi^\dagger\phi\ G^a_{\mu\nu}G^{a\mu\nu}$	$\mathcal{O}_{WW}$	$\phi^\dagger\ \hat{W}_{\mu\nu}\hat{W}^{\mu\nu}\ \phi$
$\mathcal{O}_{BB}$	$\phi^\dagger\ \hat{B}_{\mu\nu}\hat{B}^{\mu\nu}\ \phi$	$\mathcal{O}_{W}$	$(D_\mu\phi)^\dagger\hat{W}^{\mu\nu}(D_\nu\phi)$
$\mathcal{O}_{B}$	$(D_\mu\phi)^\dagger\hat{B}^{\mu\nu}(D_\nu\phi)$	$\mathcal{O}_{BW}$	$\phi^\dagger\ \hat{B}_{\mu\nu}\hat{W}^{\mu\nu}\ \phi$
$\mathcal{O}_{\phi 1}$	$(D_\mu\phi)^\dagger\ \phi\phi^\dagger\ (D^\mu\phi)$	$\mathcal{O}_{\phi 2}$	$\frac{1}{2}\partial^\mu(\phi^\dagger\phi)\partial_\mu(\phi^\dagger\phi)$
$\mathcal{O}_{3W}$	$\mathrm{Tr}\left(\hat{W}_{\mu\nu}\hat{W}^{\nu\rho}\hat{W}^\mu_\rho\right)$		
$\mathcal{O}^{(1)}_{\phi u}$	$\phi^\dagger(i\overleftrightarrow{D}_\mu\phi)(\bar{u}_R\gamma^\mu u_R)$	$\mathcal{O}^{(1)}_{\phi Q}$	$\phi^\dagger(i\overleftrightarrow{D}_\mu\phi)(\bar{Q}\gamma^\mu Q)$
$\mathcal{O}^{(1)}_{\phi d}$	$\phi^\dagger(i\overleftrightarrow{D}_\mu\phi)(\bar{d}_R\gamma^\mu d_R)$	$\mathcal{O}^{(3)}_{\phi Q}$	$\phi^\dagger(i\overleftrightarrow{D}^a_\mu\phi)\left(\bar{Q}\gamma^\mu\frac{\sigma_a}{2}Q\right)$
$\mathcal{O}^{(1)}_{\phi e}$	$\phi^\dagger(i\overleftrightarrow{D}_\mu\phi)(\bar{e}_R\gamma^\mu e_R)$		
$\mathcal{O}_{e\phi,22}$	$\phi^\dagger\phi\ \bar{L}_2\phi e_{R,2}$	$\mathcal{O}_{e\phi,33}$	$\phi^\dagger\phi\ \bar{L}_3\phi e_{R,3}$
$\mathcal{O}_{u\phi,33}$	$\phi^\dagger\phi\ \bar{Q}_3\tilde{\phi}u_{R,3}$	$\mathcal{O}_{d\phi,33}$	$\phi^\dagger\phi\ \bar{Q}_3\phi d_{R,3}$
$\mathcal{O}_{4L}$	$(\bar{L}_1\gamma_\mu L_2)\,(\bar{L}_2\gamma^\mu L_1)$		

Higgs-gauge operator definitions (Warsaw)

Operator	Definition	Operator	Definition
$\mathcal{O}_{\phi G}$	$\phi^\dagger\phi G^A_{\mu\nu}G^{A\mu\nu}$	$\mathcal{O}_W$	$\varepsilon^{IJK}W^{I\nu}_{\mu}W^{J\rho}_{\nu}W^{K\mu}_{\rho}$
$\mathcal{O}_{\phi B}$	$\phi^\dagger\phi B_{\mu\nu}B^{\mu\nu}$	$\mathcal{O}_{\phi W}$	$\phi^\dagger\phi W^I_{\mu\nu}W^{I\mu\nu}$
$\mathcal{O}_{\phi WB}$	$\phi^\dagger\tau^I\phi W^I_{\mu\nu}B^{\mu\nu}$		
$\mathcal{O}_{\phi\Box}$	$(\phi^\dagger\phi)\Box(\phi^\dagger\phi)$	$\mathcal{O}_{\phi D}$	$(\phi^\dagger D^\mu\phi)^*(\phi^\dagger D^\mu\phi)$
$\mathcal{O}_{\phi e}$	$(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{e}_i\gamma^\mu e_i)$	$\mathcal{O}_{\phi b}$	$(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{b}_i\tau^I\gamma^\mu b_i)$
$\mathcal{O}_{\phi d}$	$\sum_{i=1}^2(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{d}_i\gamma^\mu d_i)$	$\mathcal{O}_{\phi u}$	$\sum_{i=1}^2(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{u}_i\gamma^\mu u_i)$
$\mathcal{O}^{(1)}_{\phi q}$	$\sum_{i=1}^2(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{q}_i\gamma^\mu q_i)$	$\mathcal{O}^{(3)}_{\phi q}$	$\sum_{i=1}^2(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{q}_i\tau^I\gamma^\mu q_i)$
$\mathcal{O}^{(1)}_{\phi l}$	$(\phi^\dagger i\overleftrightarrow{D}_\mu\phi)(\bar{l}\gamma^\mu l)$	$\mathcal{O}^{(3)}_{\phi l}$	$(\phi^\dagger i\overleftrightarrow{D}^I_\mu\phi)(\bar{l}\tau^I\gamma^\mu l)$
$\mathcal{O}_{d\phi,33}$	$(\phi^\dagger\phi)(\bar{Q}_3 b\phi)$	$\mathcal{O}_{u\phi,33}$	$(\phi^\dagger\phi)(\bar{Q}_3 t\phi)$
$\mathcal{O}_{e\phi,22}$	$(\phi^\dagger\phi)(\bar{l}_2\mu\phi)$	$\mathcal{O}_{e\phi,33}$	$(\phi^\dagger\phi)(\bar{l}_3\tau\phi)$
$\mathcal{O}_{ll}$	$(\bar{l}\gamma_\mu l)(\bar{l}\gamma^\mu l)$		

Full top dataset

Experiment	Energy [TeV]	$\mathcal{L}$ [fb^{-1}]	Channel	Observable	# Bins	New	Likelihood	QCD k-factor
CMS [79]	8	19.7	$e\mu$	$\sigma_{t\bar{t}}$				[80]
ATLAS [81]	8	20.2	lj	$\sigma_{t\bar{t}}$				[80]
CMS [82]	13	137	lj	$\sigma_{t\bar{t}}$		✓		[80]
CMS [83]	13	35.9	ll	$\sigma_{t\bar{t}}$				[80]
ATLAS [84]	13	36.1	ll	$\sigma_{t\bar{t}}$		✓		[80]
ATLAS [85]	13	36.1	aj	$\sigma_{t\bar{t}}$		✓		[80]
ATLAS [47]	13	139	lj	$\sigma_{t\bar{t}}$		✓	✓	[80]
CMS [86]	13.6	1.21	ll, lj	$\sigma_{t\bar{t}}$		✓		[86]
CMS [87]	8	19.7	lj	$\frac{1}{\sigma}\frac{d\sigma}{dp_T^t}$	7			[88–90]
CMS [87]	8	19.7	ll	$\frac{1}{\sigma}\frac{d\sigma}{dp_T^t}$	5			[88–90]
ATLAS [91]	8	20.3	lj	$\frac{1}{\sigma}\frac{d\sigma}{dm_{t\bar{t}}}$	7			[88–90]
CMS [82]	13	137	lj	$\frac{1}{\sigma}\frac{d\sigma}{dm_{t\bar{t}}}$	15	✓		[45]
CMS [92]	13	35.9	ll	$\frac{1}{\sigma}\frac{d\sigma}{d\Delta y_{t\bar{t}}}$	8			[88–90]
ATLAS [93]	13	36	lj	$\frac{1}{\sigma}\frac{d\sigma}{dm_{t\bar{t}}}$	9	✓		[45]
ATLAS [94]	13	139	aj, high-p_T	$\frac{1}{\sigma}\frac{d\sigma}{dm_{t\bar{t}}}$	13	✓		
CMS [95]	8	19.7	lj	A_C				[96]
CMS [97]	8	19.5	ll	A_C				[96]
ATLAS [98]	8	20.3	lj	A_C				[96]
ATLAS [99]	8	20.3	ll	A_C				[96]
CMS [100]	13	138	lj	A_C		✓		[96]
ATLAS [101]	13	139	lj	A_C		✓		[96]
ATLAS [48]	13	139		$\sigma_{t\bar{t}Z}$		✓	✓	[102]
CMS [103]	13	77.5		$\sigma_{t\bar{t}Z}$				[102]
CMS [104]	13	35.9		$\sigma_{t\bar{t}W}$				[102]
ATLAS [105]	13	36.1		$\sigma_{t\bar{t}W}$		✓		[102]
CMS [106]	8	19.7		$\sigma_{t\bar{t}\gamma}$		✓		
ATLAS [107]	8	20.2		$\sigma_{t\bar{t}\gamma}$		✓		

Exp.	$\sqrt{s}$ [TeV]	$\mathcal{L}$ [fb^{-1}]	Channel	Observable	# Bins	New	Likelihood	QCD k-factor
ATLAS [108]	7	4.59	t-ch	$\sigma_{tq+\bar{t}q}$				
CMS [109]	7	1.17 (e), 1.56 (μ)	t-ch	$\sigma_{tq+\bar{t}q}$				
ATLAS [110]	8	20.2	t-ch	σ_{tq}, $\sigma_{\bar{t}q}$				
CMS [111]	8	19.7	t-ch	σ_{tq}, $\sigma_{\bar{t}q}$				
ATLAS [112]	13	3.2	t-ch	σ_{tq}, $\sigma_{\bar{t}q}$				[113]
CMS [114]	13	2.2	t-ch	σ_{tq}, $\sigma_{\bar{t}q}$				[113]
CMS [115]	13	35.9	t-ch	$\frac{1}{\sigma}\frac{d\sigma}{d\lvert p_{T,t}\rvert}$	5	✓		
CMS [116]	7	5.1	s-ch	$\sigma_{t\bar{b}+\bar{t}b}$				
CMS [116]	8	19.7	s-ch	$\sigma_{t\bar{b}+\bar{t}b}$				
ATLAS [117]	8	20.3	s-ch	$\sigma_{t\bar{b}+\bar{t}b}$				
ATLAS [49]	13	139	s-ch	$\sigma_{t\bar{b}+\bar{t}b}$		✓	✓	
ATLAS [118]	7	2.05	tW ($2l$)	$\sigma_{tW+\bar{t}W}$				
CMS [119]	7	4.9	tW ($2l$)	$\sigma_{tW+\bar{t}W}$				
ATLAS [120]	8	20.3	tW ($2l$)	$\sigma_{tW+\bar{t}W}$				
ATLAS [121]	8	20.2	tW ($1l$)	$\sigma_{tW+\bar{t}W}$		✓		
CMS [122]	8	12.2	tW ($2l$)	$\sigma_{tW+\bar{t}W}$				
ATLAS [123]	13	3.2	tW ($1l$)	$\sigma_{tW+\bar{t}W}$				
CMS [124]	13	35.9	tW ($e\mu j$)	$\sigma_{tW+\bar{t}W}$				
CMS [125]	13	36	tW ($2l$)	$\sigma_{tW+\bar{t}W}$		✓		
ATLAS [126]	13	36.1	tZ	σ_{tZq}				
ATLAS [127]	7	1.04		F_0,F_L				
CMS [128]	7	5		F_0,F_L				
ATLAS [129]	8	20.2		F_0,F_L				
CMS [130]	8	19.8		F_0,F_L				
ATLAS [131]	13	139		F_0,F_L		✓		

SFitter - Likelihood

Global Likelihood

$$L_{\text{excl,full}} = \prod_c \text{Pois}(d_c \,|\, p_c(C,\theta,b))\ \text{Pois}(b_{CR_c} \,|\, b_c k_c) \prod_i \mathscr{C}_i(\theta_{i,c}, \sigma_{i,c})$$

Correlations

$$C_{ij} = \frac{\sum_{\text{syst}} \rho_{ij}\ \sigma_{i,\text{syst}}\sigma_{j,\text{syst}}}{\sigma_{i,\text{exp}}\sigma_{j,\text{exp}}} \qquad \text{with} \qquad \sigma^2_{i,\text{exp}} = \sum_{\text{syst}} \sigma^2_{i,\text{syst}} + \sum_{\text{pois}} \sigma^2_{i,\text{pois}}$$

➡ **Assumption:** Fully correlated systematics between measurements

Systematic uncertainties
Beam
Background (Separate for each channel)
ETmis
Jets
Leptons
LightTagging
Luminosity
Pileup
Trigger
Tune
bTagging
partonShower
tTagging
tauTagging

SFitter - Likelihood

Global Likelihood

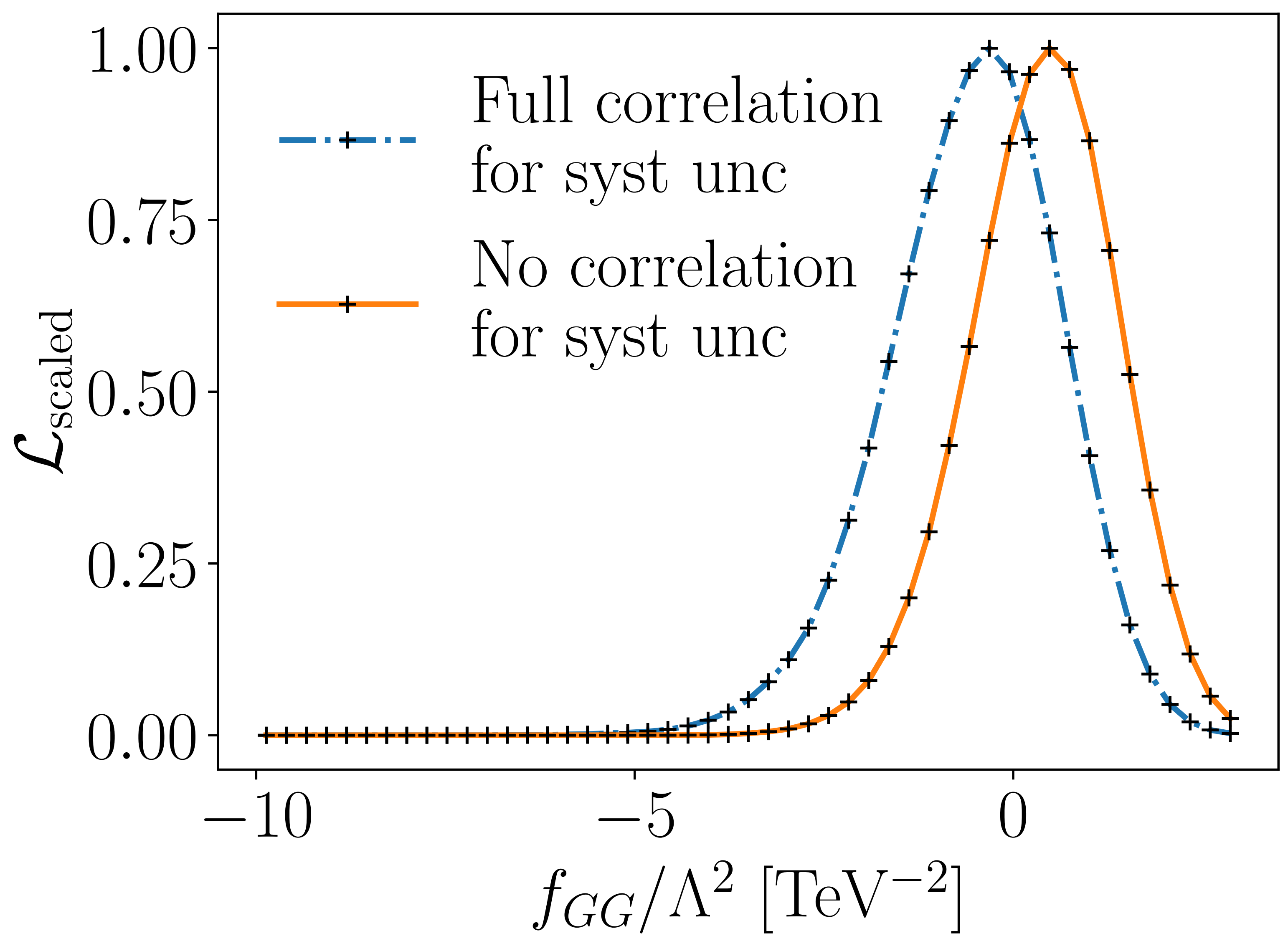
$$L_{\text{excl,full}} = \prod_c \text{Pois}(d_c \,|\, p_c(C,\theta,b))\; \text{Pois}(b_{CR_c} \,|\, b_c k_c) \prod_i \mathscr{C}_i(\theta_{i,c}, \sigma_{i,c})$$

Correlations

$$C_{ij} = \frac{\sum_{\text{syst}} \rho_{ij}\; \sigma_{i,\text{syst}}\sigma_{j,\text{syst}}}{\sigma_{i,\text{exp}}\sigma_{j,\text{exp}}} \qquad \text{with} \qquad \sigma^2_{i,\text{exp}} = \sum_{\text{syst}} \sigma^2_{i,\text{syst}} + \sum_{\text{pois}} \sigma^2_{i,\text{pois}}$$

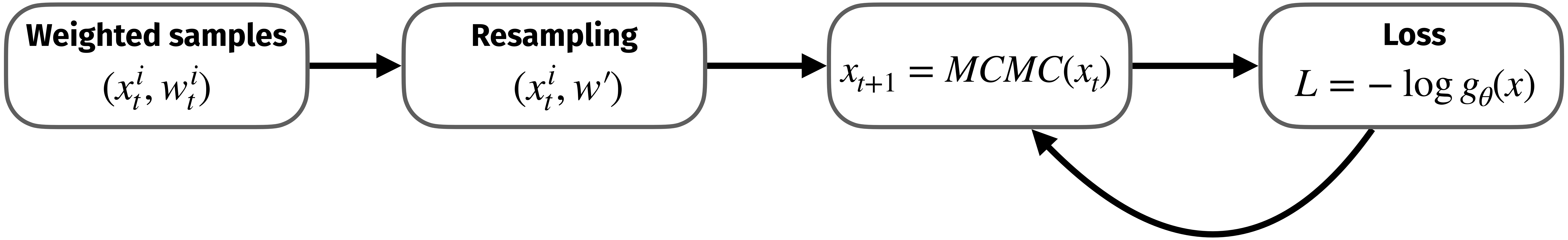
➡ **Assumption:** Fully correlated systematics between measurements

[2208.08454]



Pre-training

- Pre-train on few samples using log-likelihood loss
- Reuse pre-scaling samples



- Find a good **starting point** for the training