Profile Likelihoods on ML-Steroids

Accelerating global SMEFT fits using neural importance sampling

Nikita Schmal
05/11/2024, ML4Jets 2024

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

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A brief (SMEFT) history of SFITTER

- Used for various global SMEFT analyses
  - Higgs, EWPOs, Di-Boson data [1505.05516, 1812.07587, 2208.08454]
  - Top data (including public likelihoods) [1910.03606, 2312.12502]
- **Fully correlated** systematic uncertainties within experiments
- Allows for both **profiling and marginalisation** methods
- Mapping of likelihood using MCMC
- **Goal:** Do this, but faster and better

SMEFT

- **SMEFT**: model agnostic approach for BSM

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

- operators up to **dimension 6**, contributions to quadratic order
- Make SMEFT predictions **differentiable** and fast on a **GPU**

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

  - Expressed as **simple bilinear operation**

SFitter dataset

- Look at **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
- and at **Higgs** sector with **19 Wilson coefficients** [2208.08454]
  - 311 Higgs datapoints
  - 43 Di-Boson datapoints
  - 14 EWPOs (linear SMEFT contr.)
  - 4 high kinematic measurements

SFITTER likelihood

- Construct the likelihood for a single measurement

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

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

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

- Remove nuisance parameters via **profiling**

$$L_{\text{prof}}(x) = \max_{\theta,b} \mathscr{L}_{\text{excl}}$$

SFitter likelihood

- Split into 3 separate contributions

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

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

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

- Combined using an approximate formula

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

The five steps to happiness

- How to efficiently sample from this likelihood?
- MCMC too slow, cannot be parallelized as is

$p(x)$

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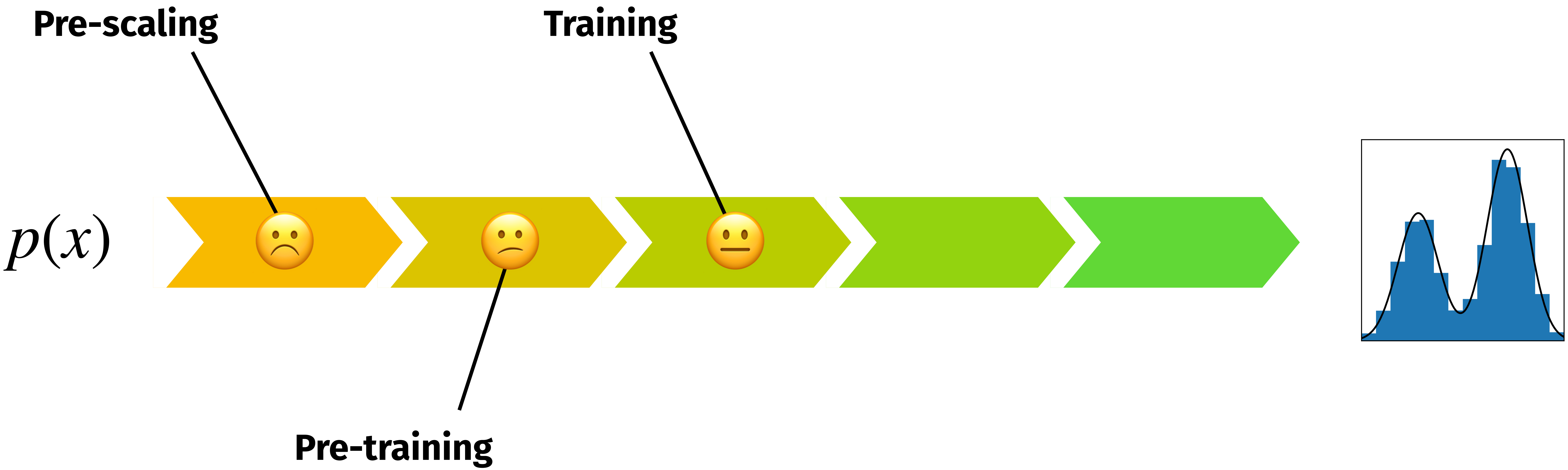

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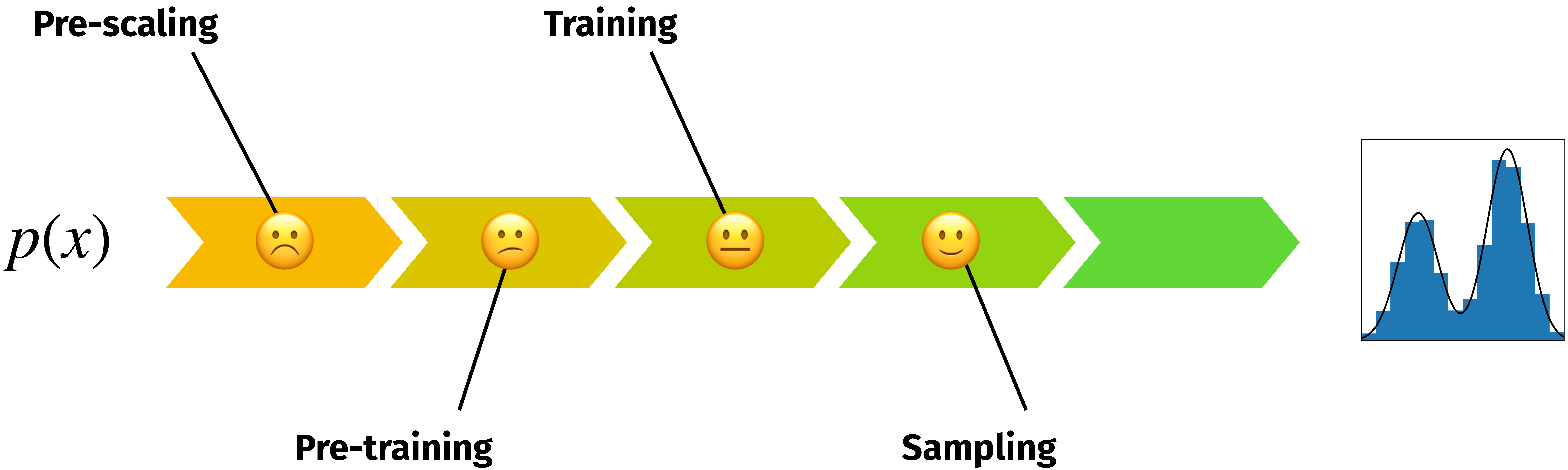

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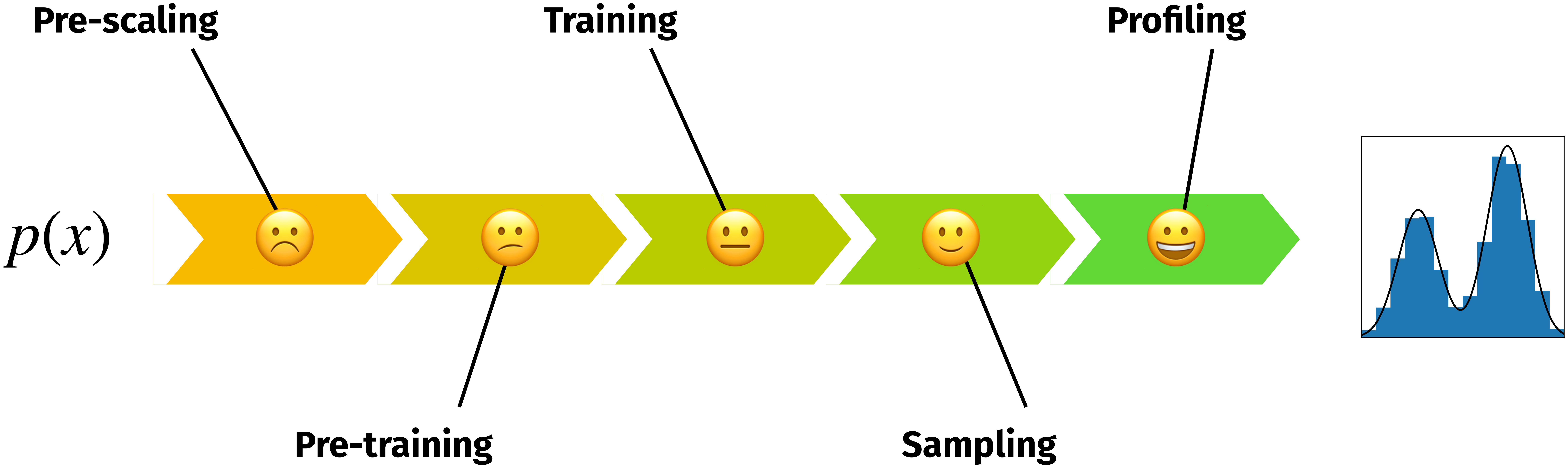

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- Use annealed importance sampling (AIS) [Neal, 2001]

$$\log p_t(x) = (1-\beta_t)\log p_0(x) + \beta_t \log p_T(x) \qquad \text{with} \qquad \beta_t = \frac{t}{T} \quad \text{and} \quad t = 1,\ldots,T$$

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Samples

$x_0 \sim p_0 = \mathcal{N}_{0,\sigma}(x_0)$

$w_0 = 1$

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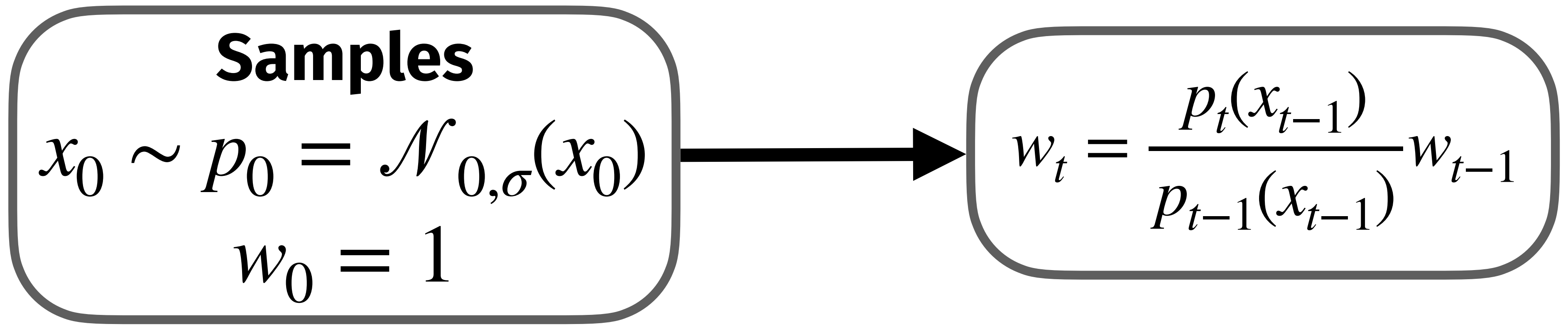

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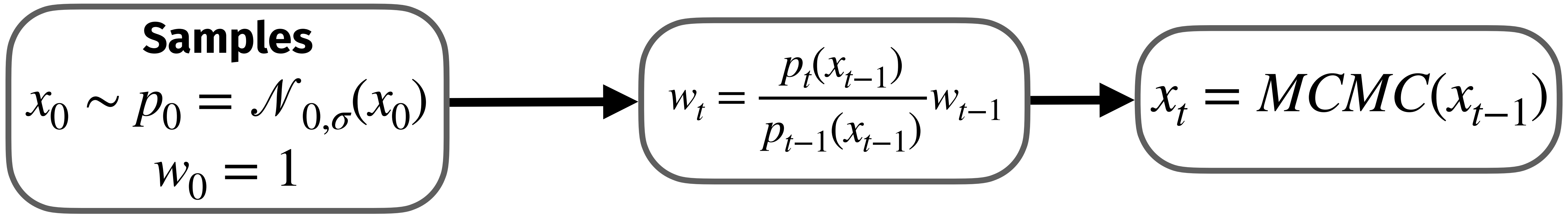

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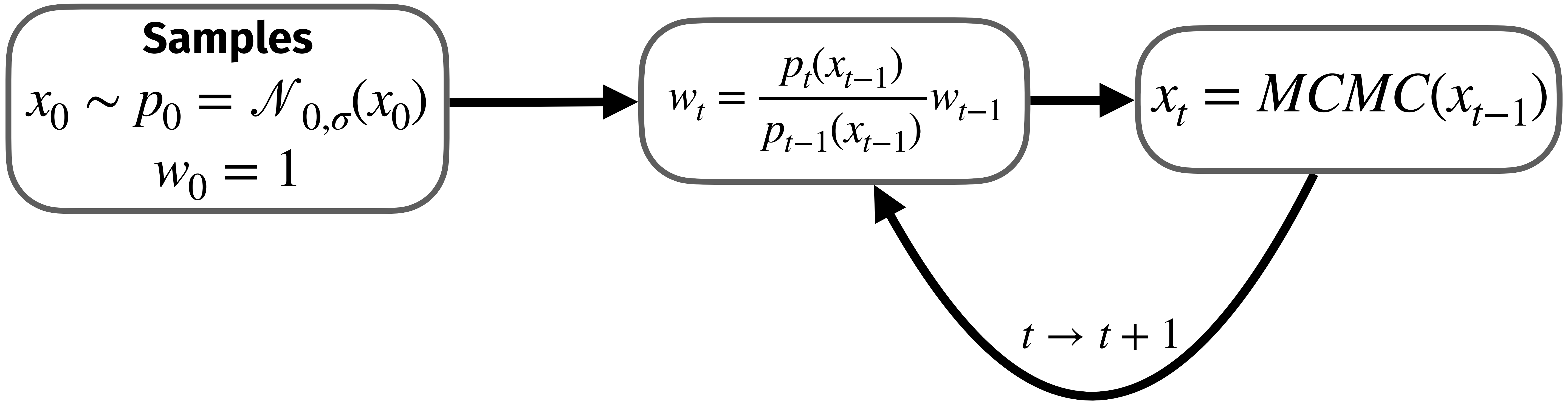

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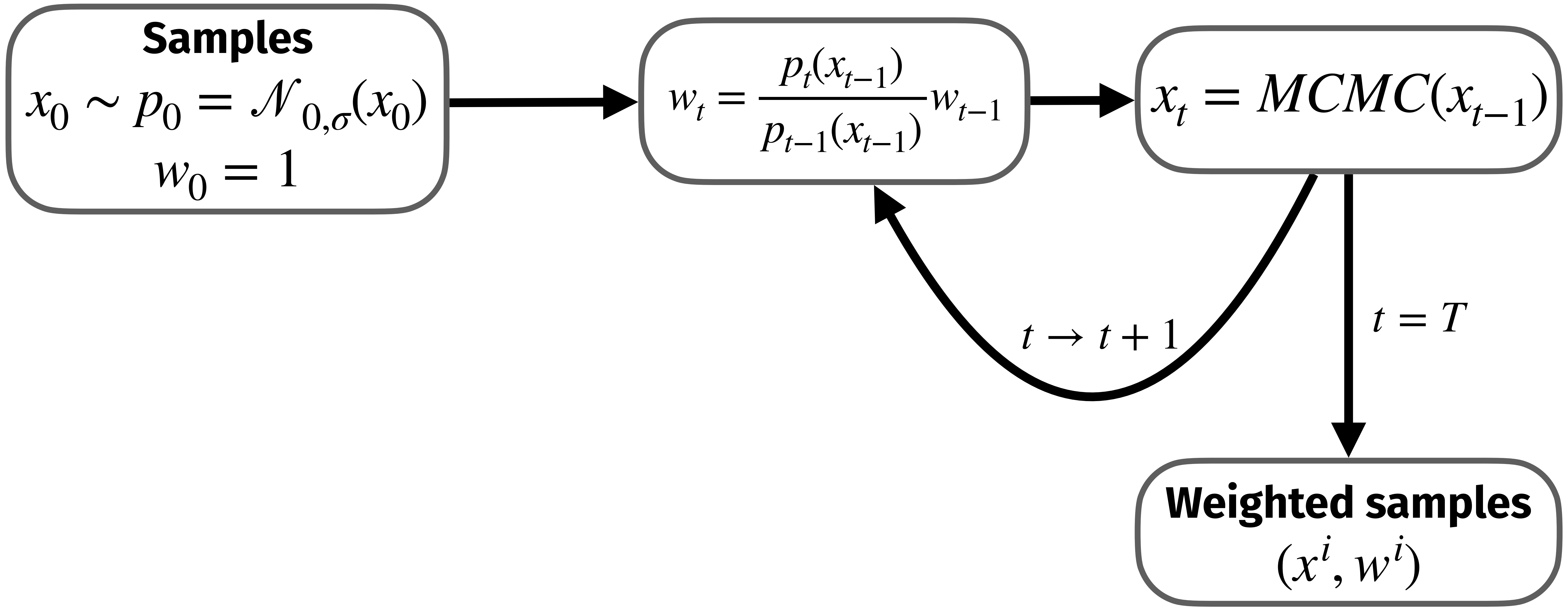

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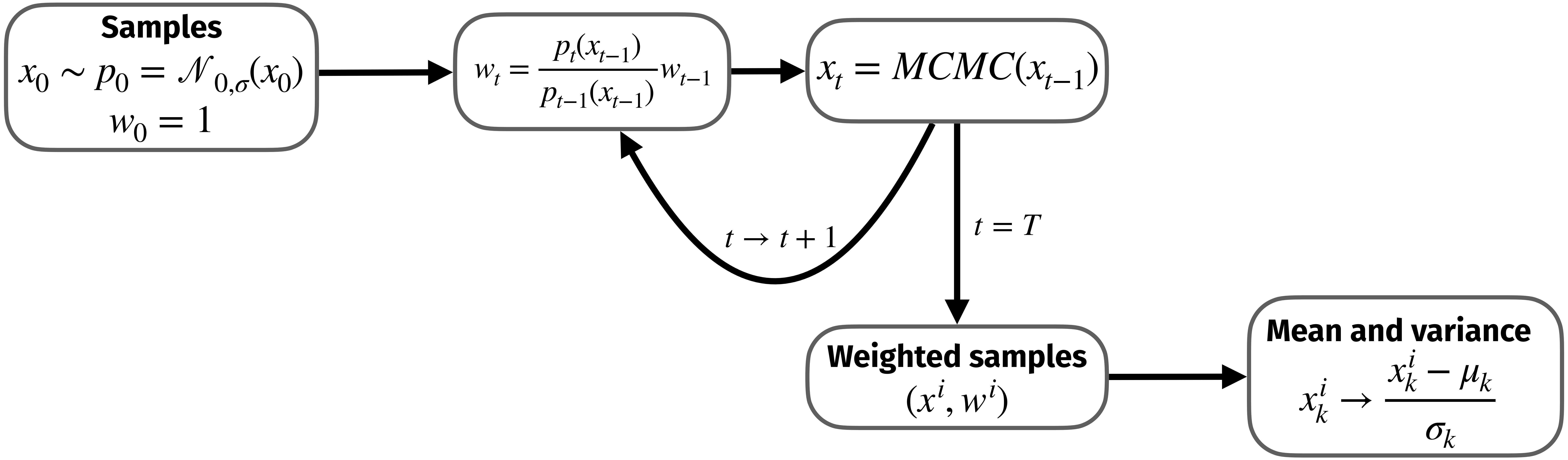
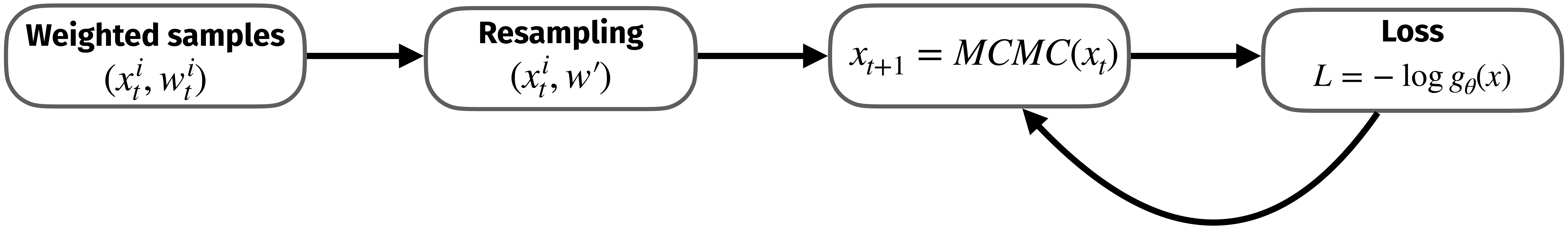


- Find a good starting point for the training of our flow
- Pre-train on small number of samples using log-likelihood loss

$$L = -\log g_\theta(x)$$

- We use the samples from our pre-scaling



- How does the main training work?

Variance loss

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

Optimal proposal

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

Gradient

$$\nabla_\theta L = \langle \nabla_\theta \log f_\theta(x) \rangle_{x \sim q(x)} = - \langle \nabla_\theta \log g_\theta(x) \rangle_{x \sim q(x)}$$

- Sampling directly from $f_\theta(x)$ is **intractable**

[Midgley et al. 2208.01893]

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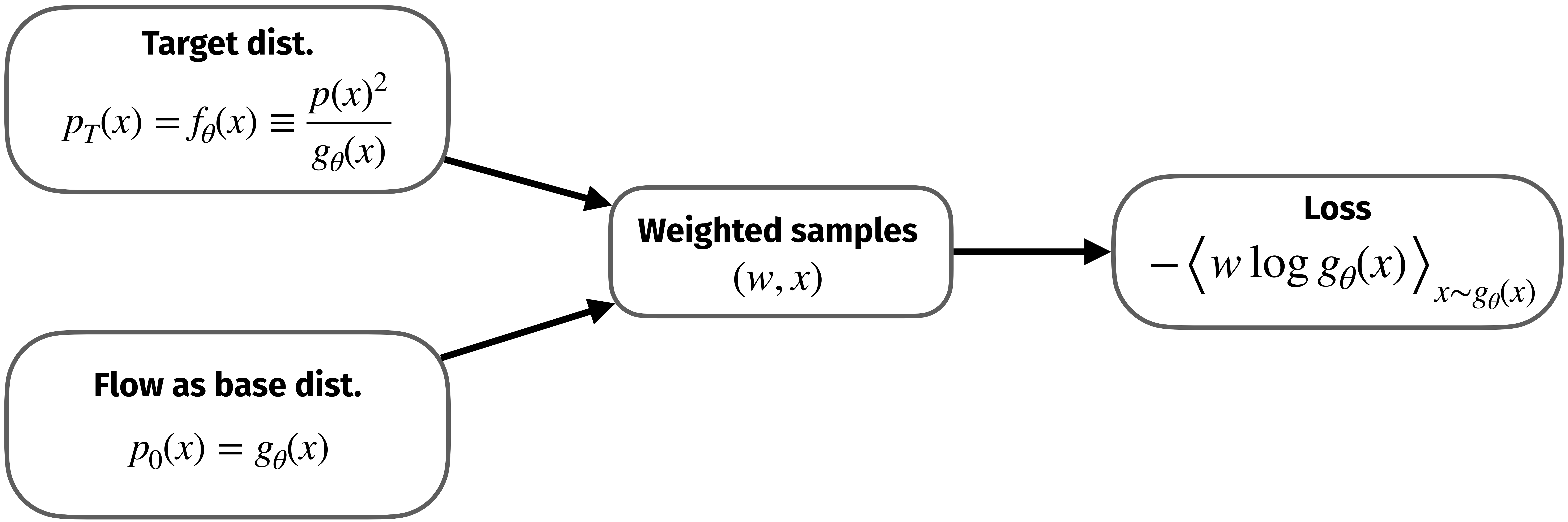
- Again annealed importance sampling can help



- Simple loss after combining AIS and our flow

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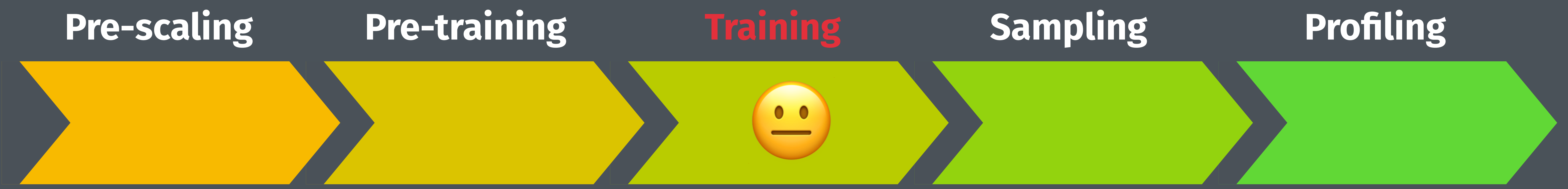
$L_{\text{buff}} = \left\langle \frac{q_\theta(x)}{q_{\hat{\theta}}(x)} \log q_\theta(x) \right\rangle$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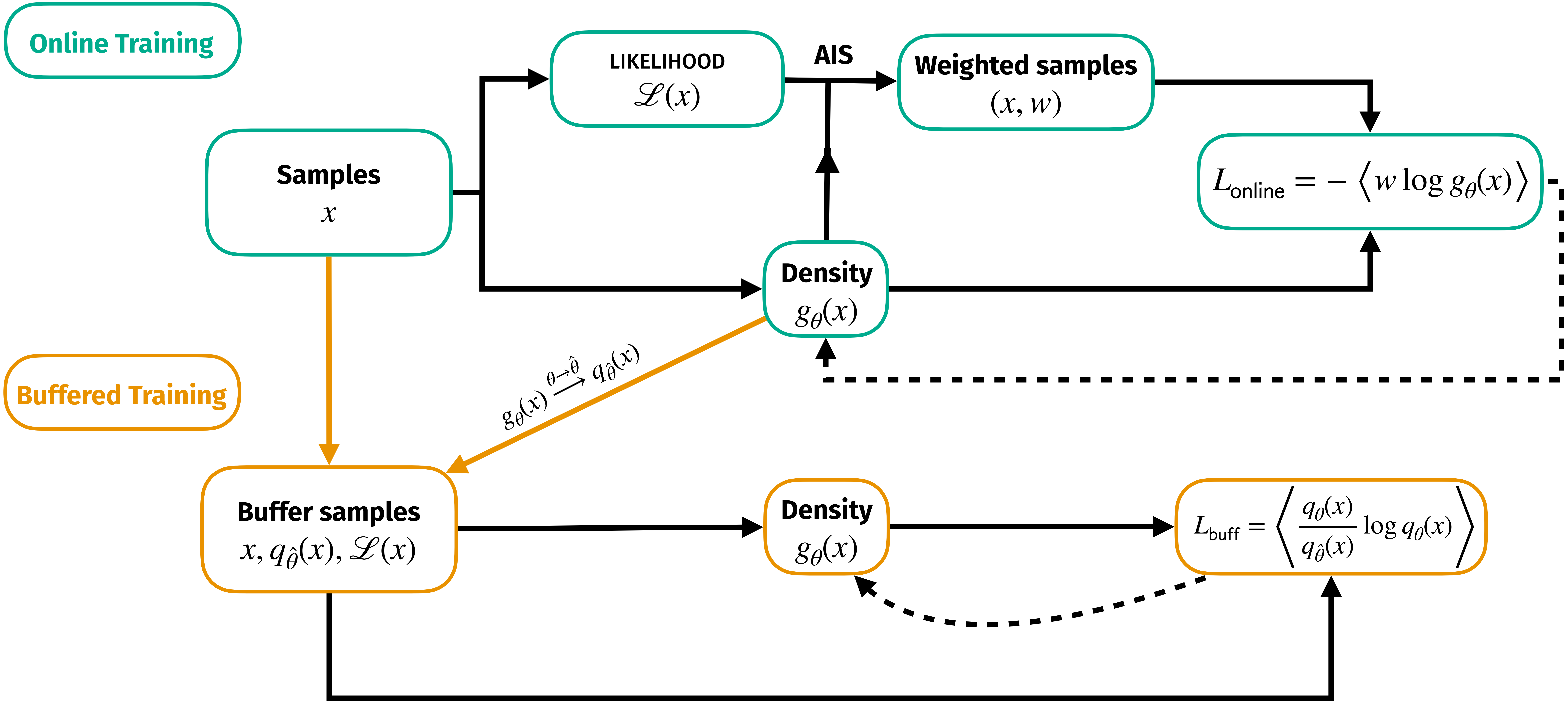
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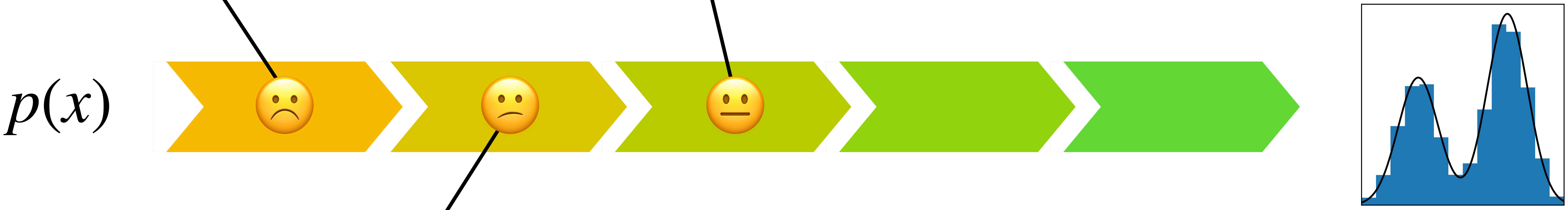
The final steps to happiness

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



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

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

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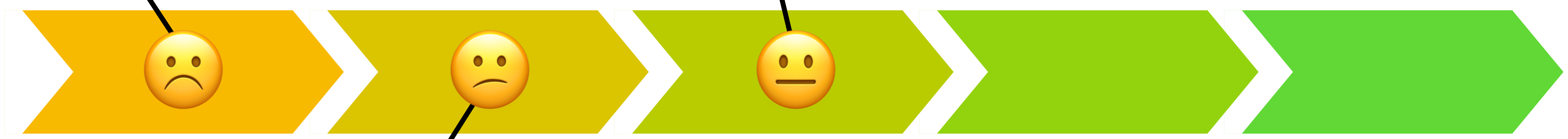

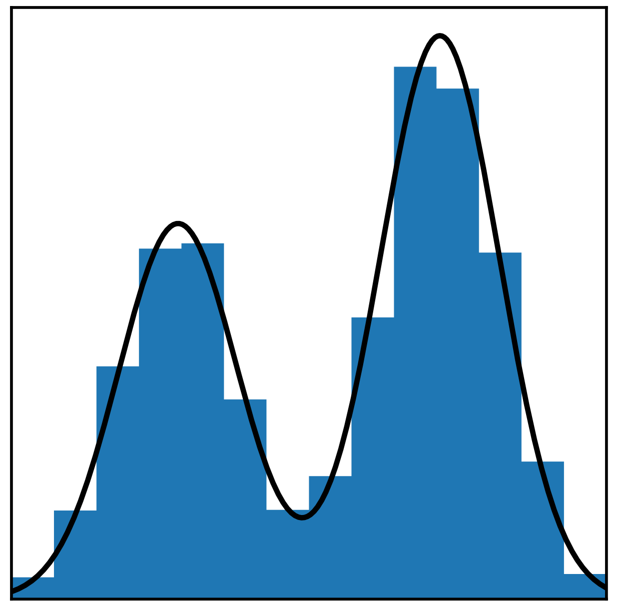

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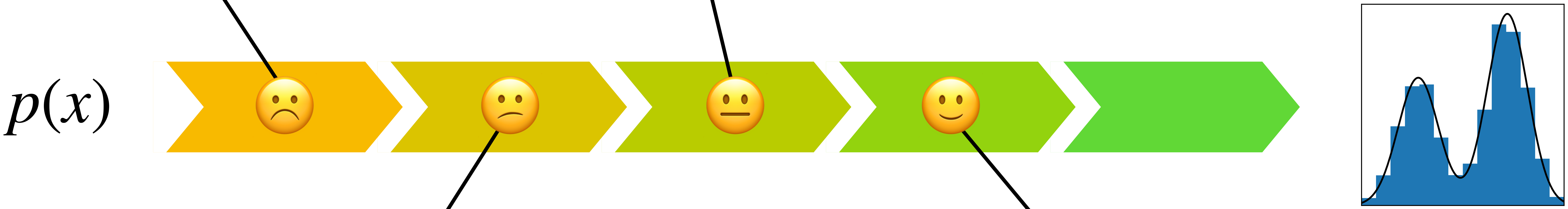

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Sampling
- generate weighted samples
- keep track of points with highest likelihood in each bin

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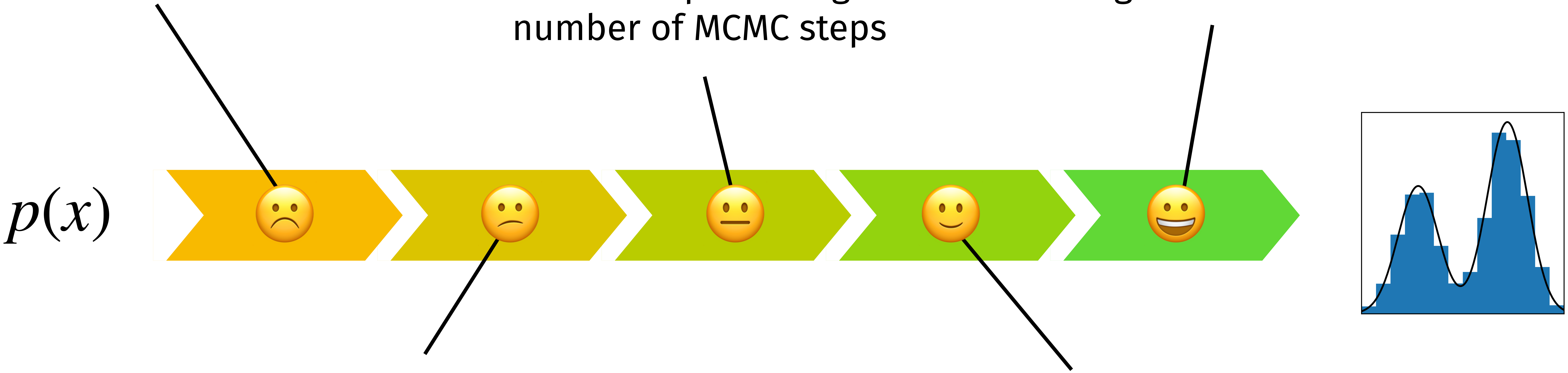
Profiling
- run maximization algorithm for each bin (L-BFGS)
- use gradient information



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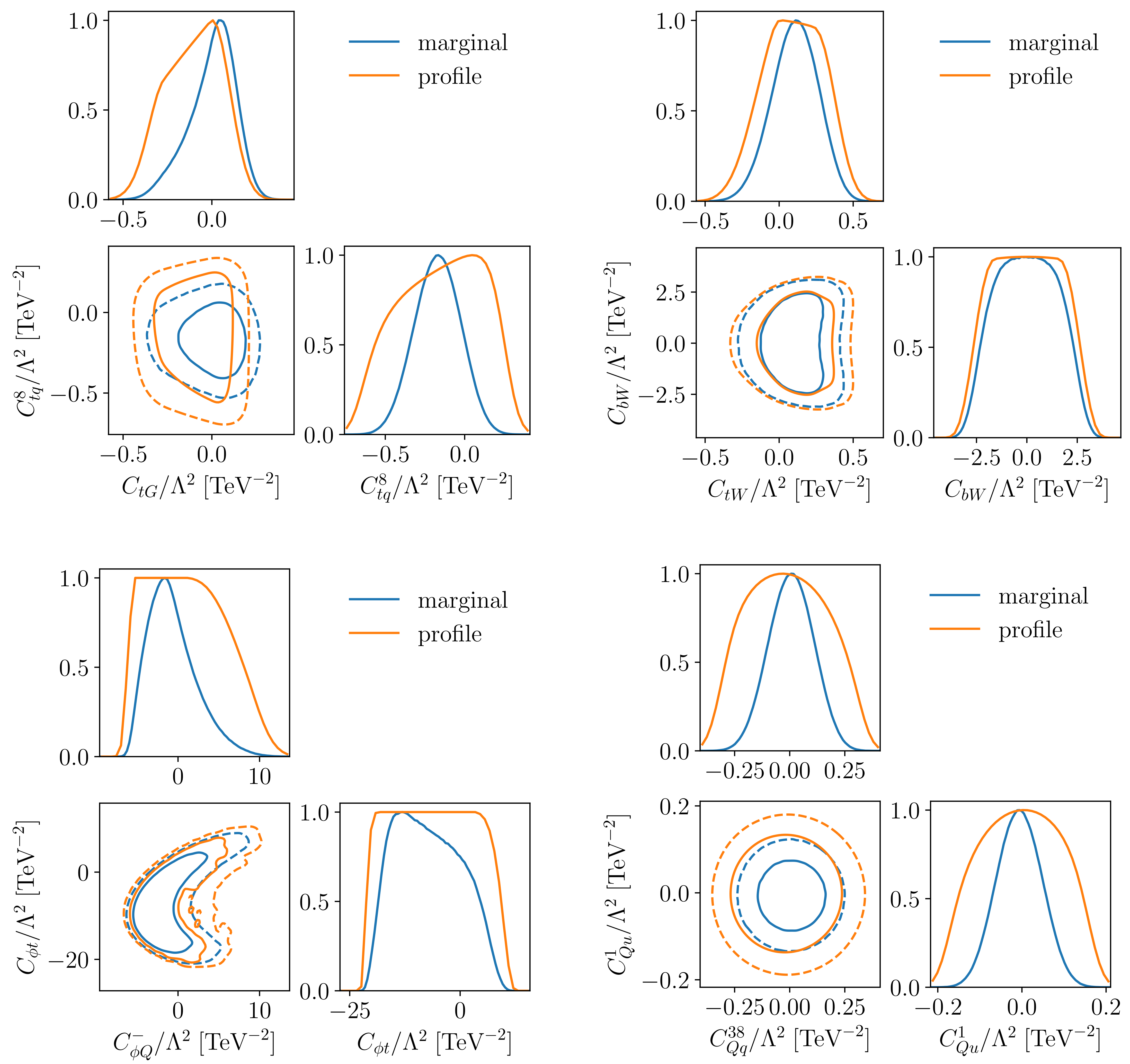
- Relatively simple top likelihood, mostly unfolded data
- Large effect from **theory uncertainties**
- **Smooth results** for both profiling and marginalization



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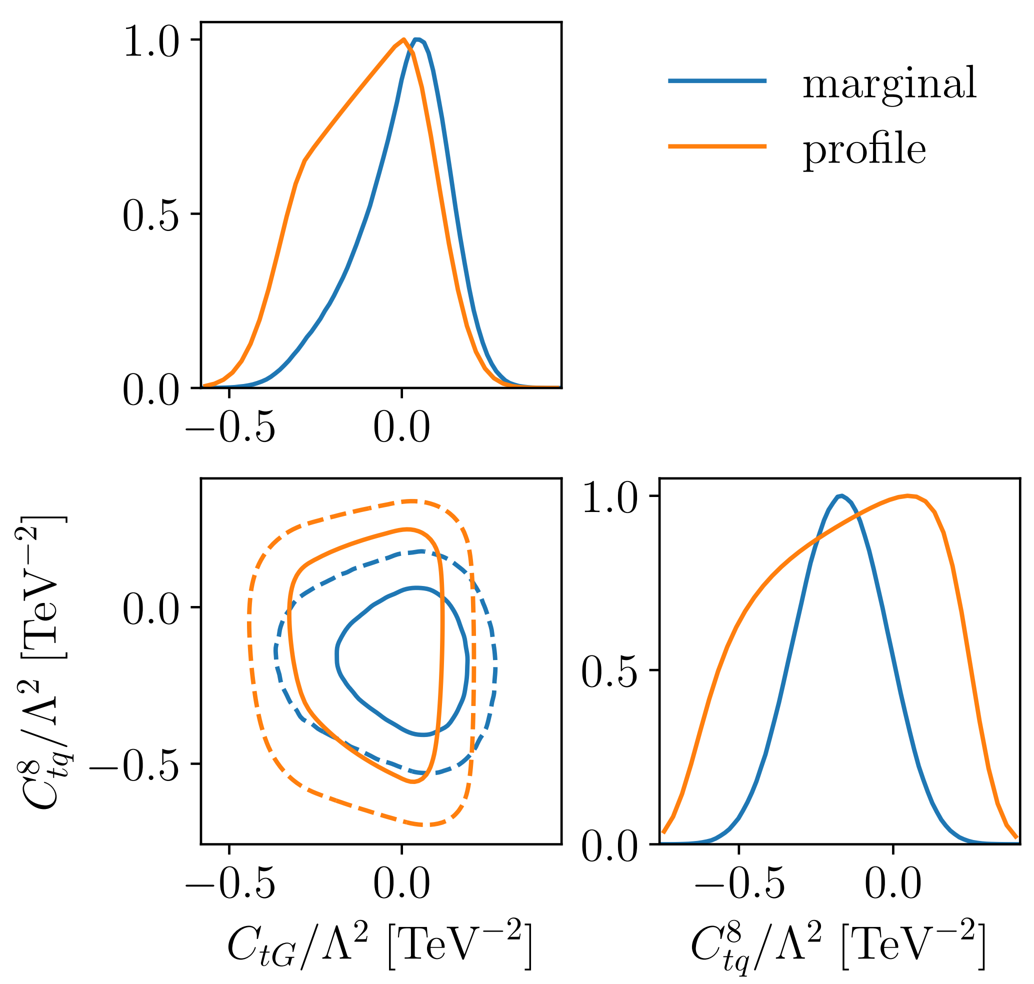
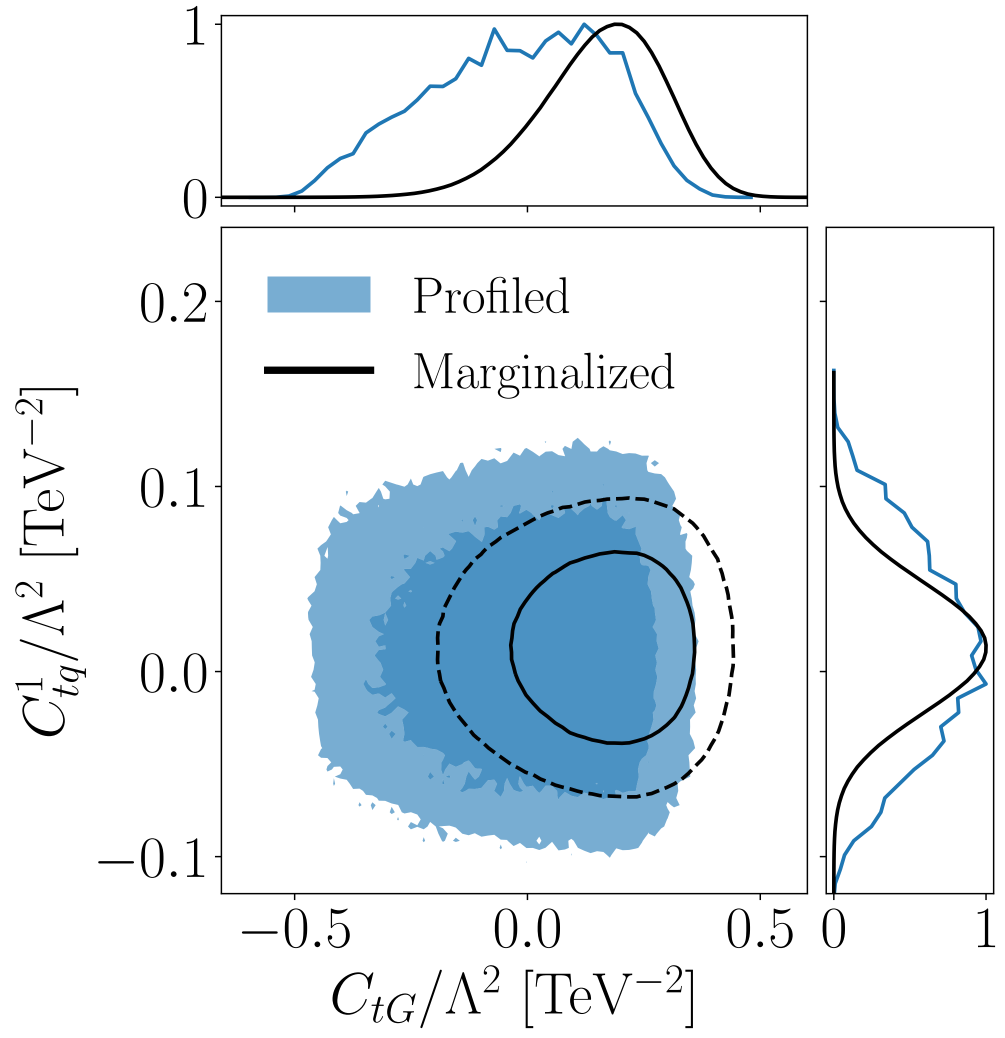
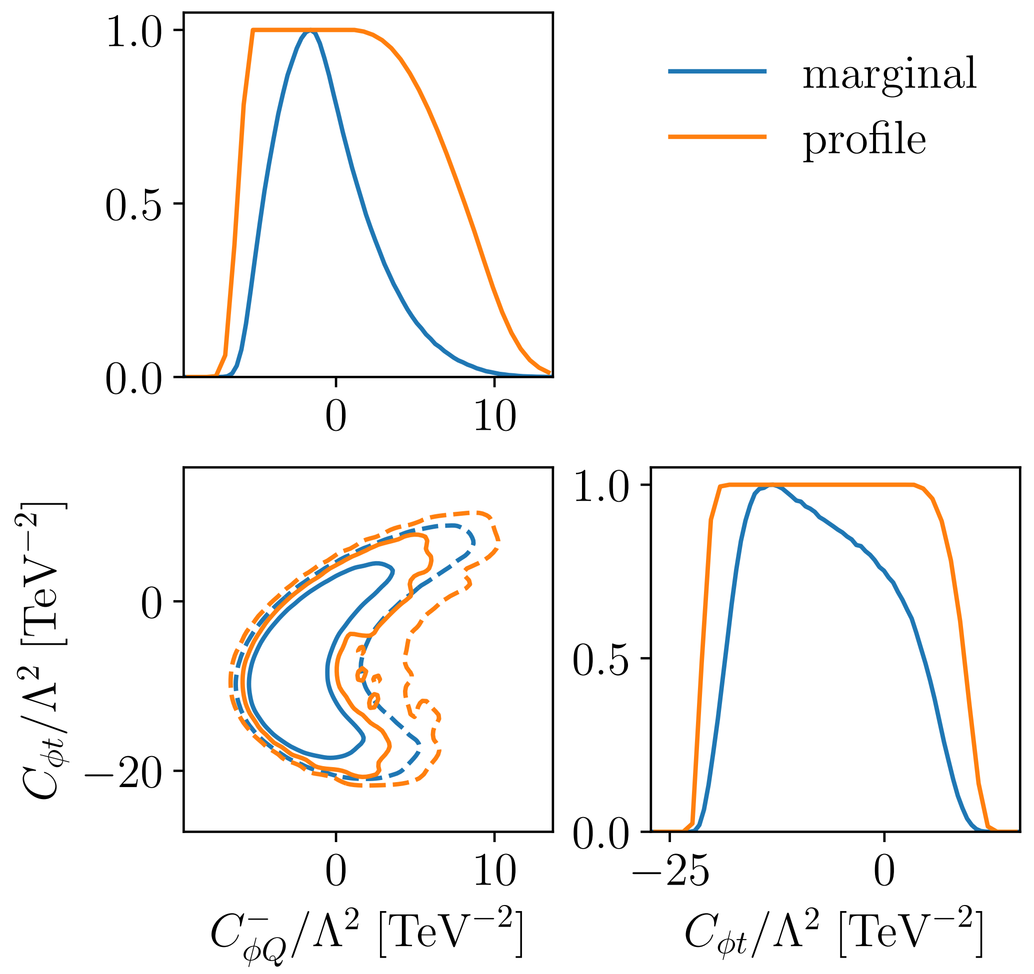
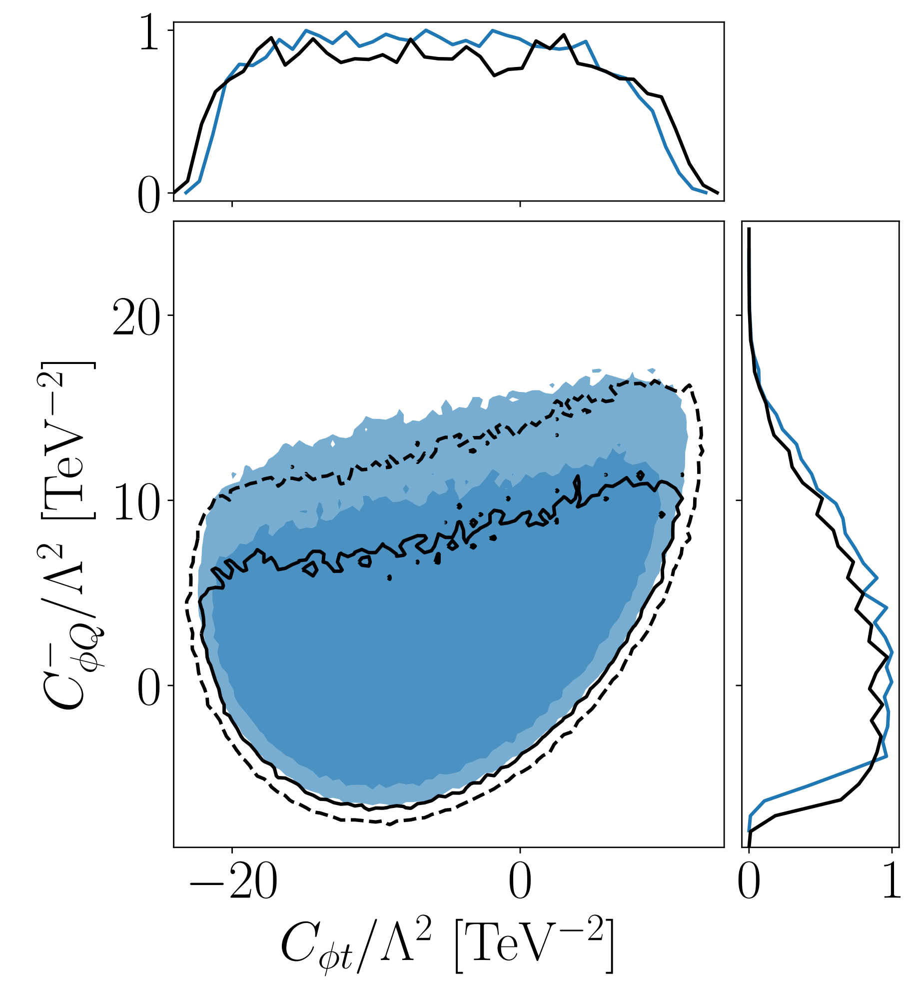
[2312.12502]









Performance

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

	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
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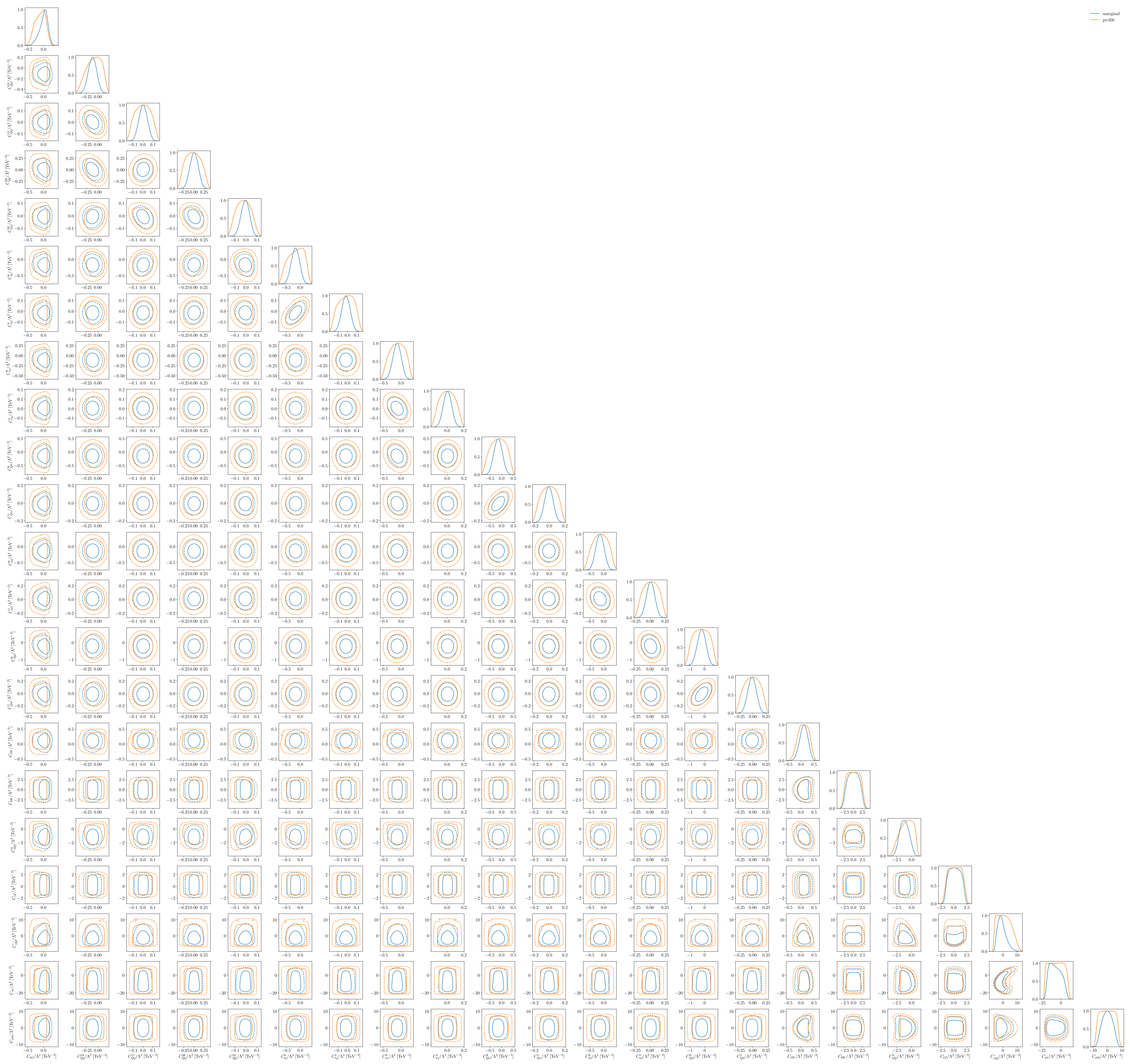

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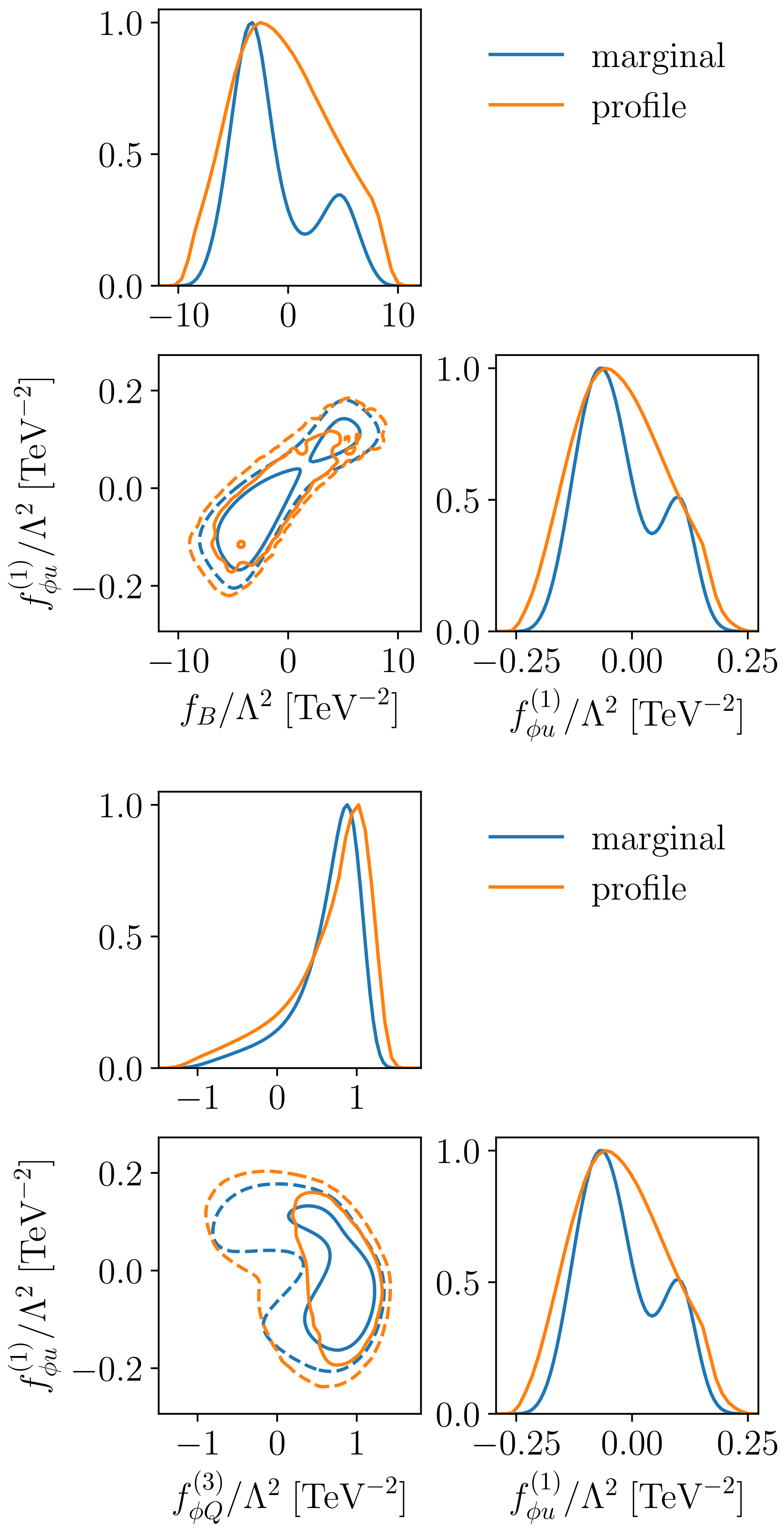
Results

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



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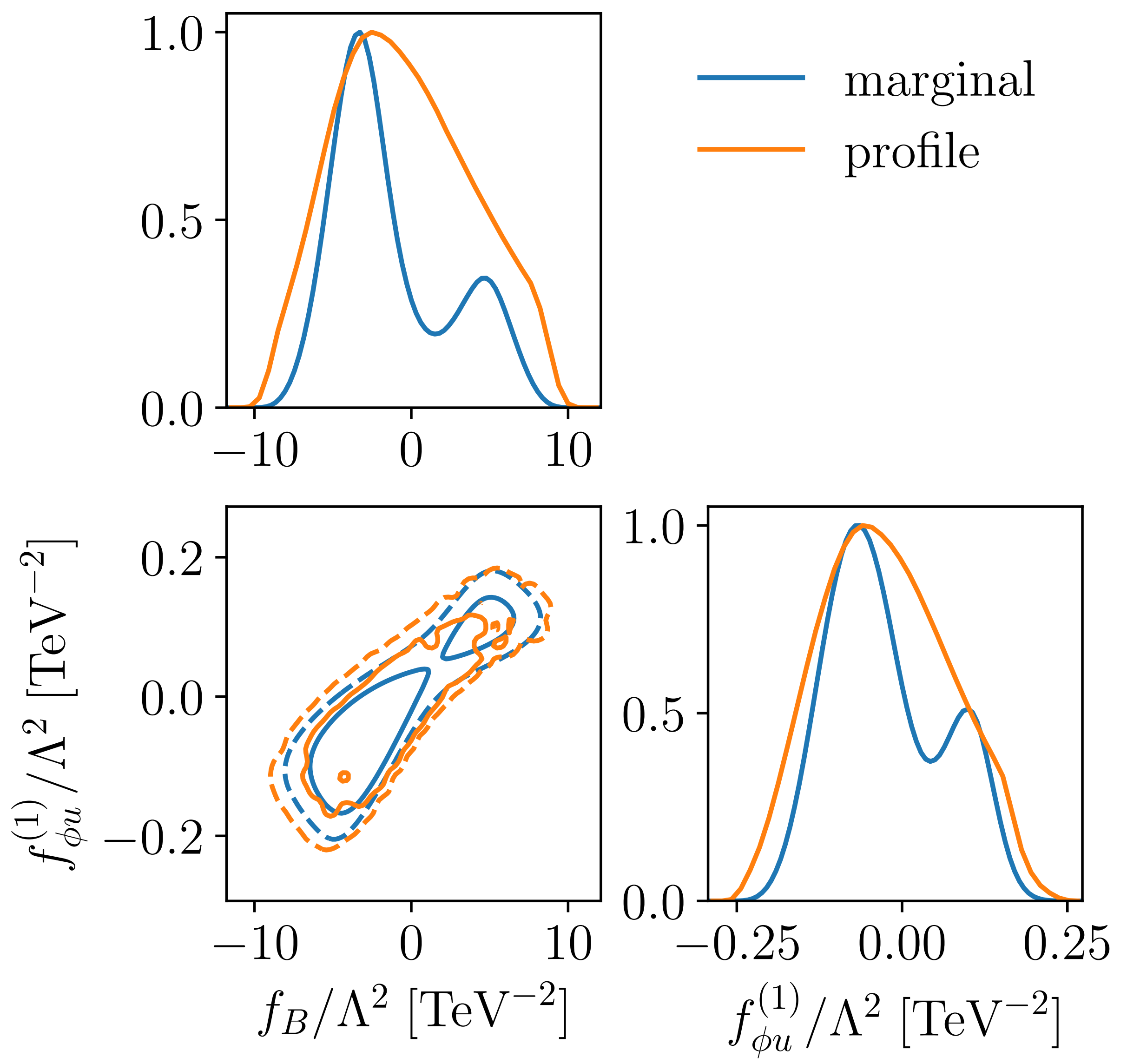

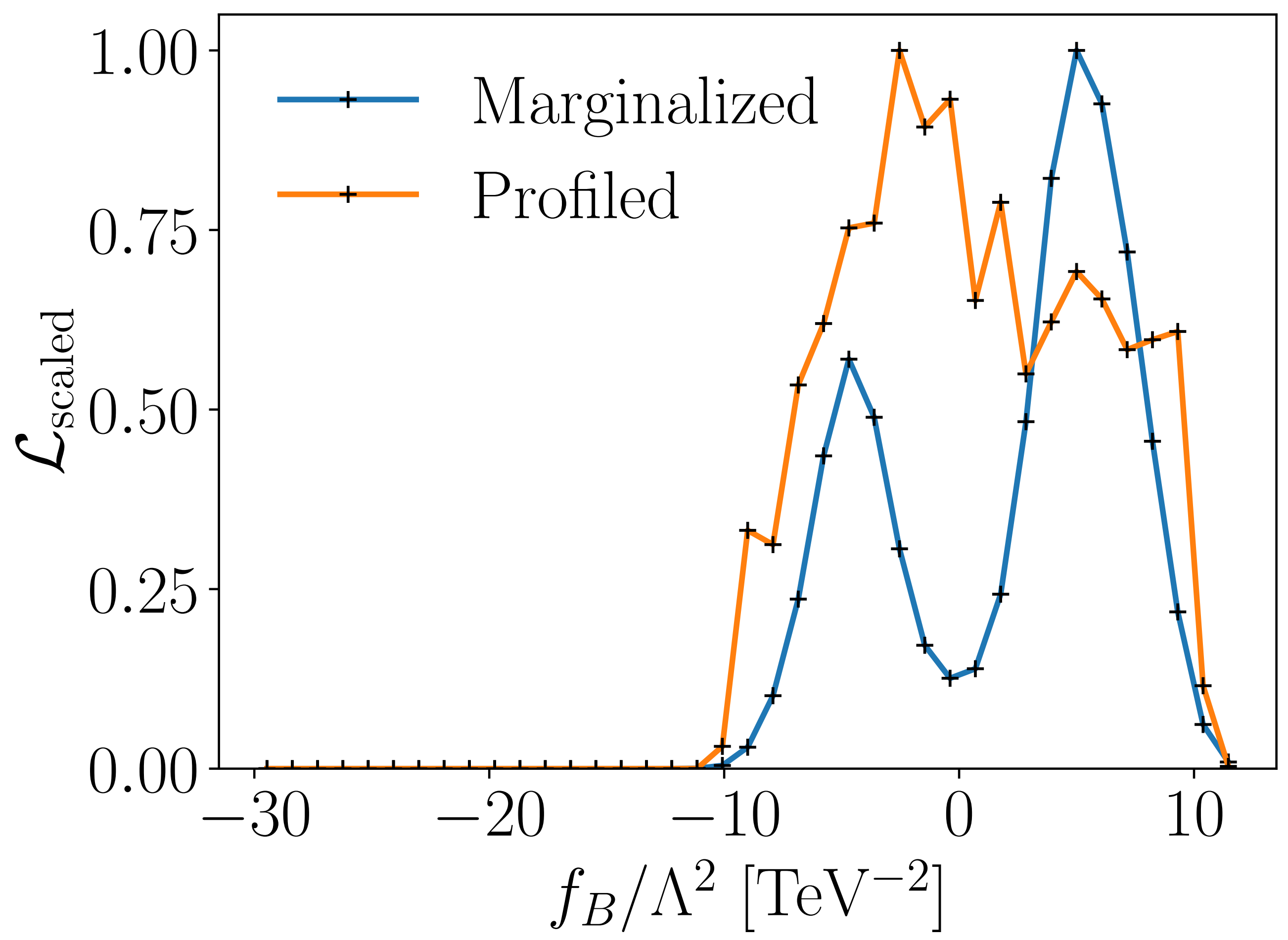

[2208.08454]

Performance

- Already requires **4x CPUs** for decent results
- Slightly longer training required, still **significantly faster** even for complicated likelihoods

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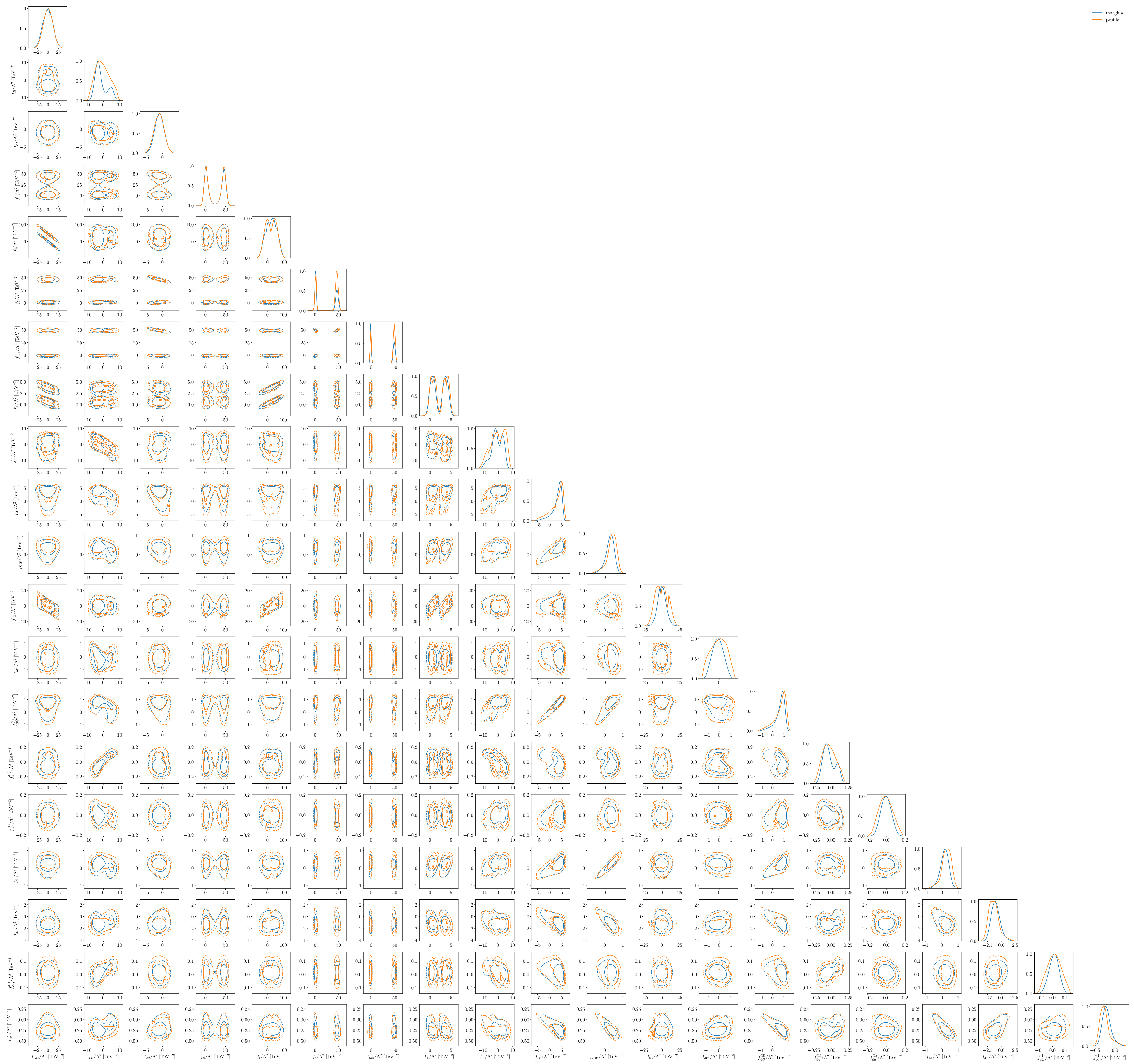

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Performance

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

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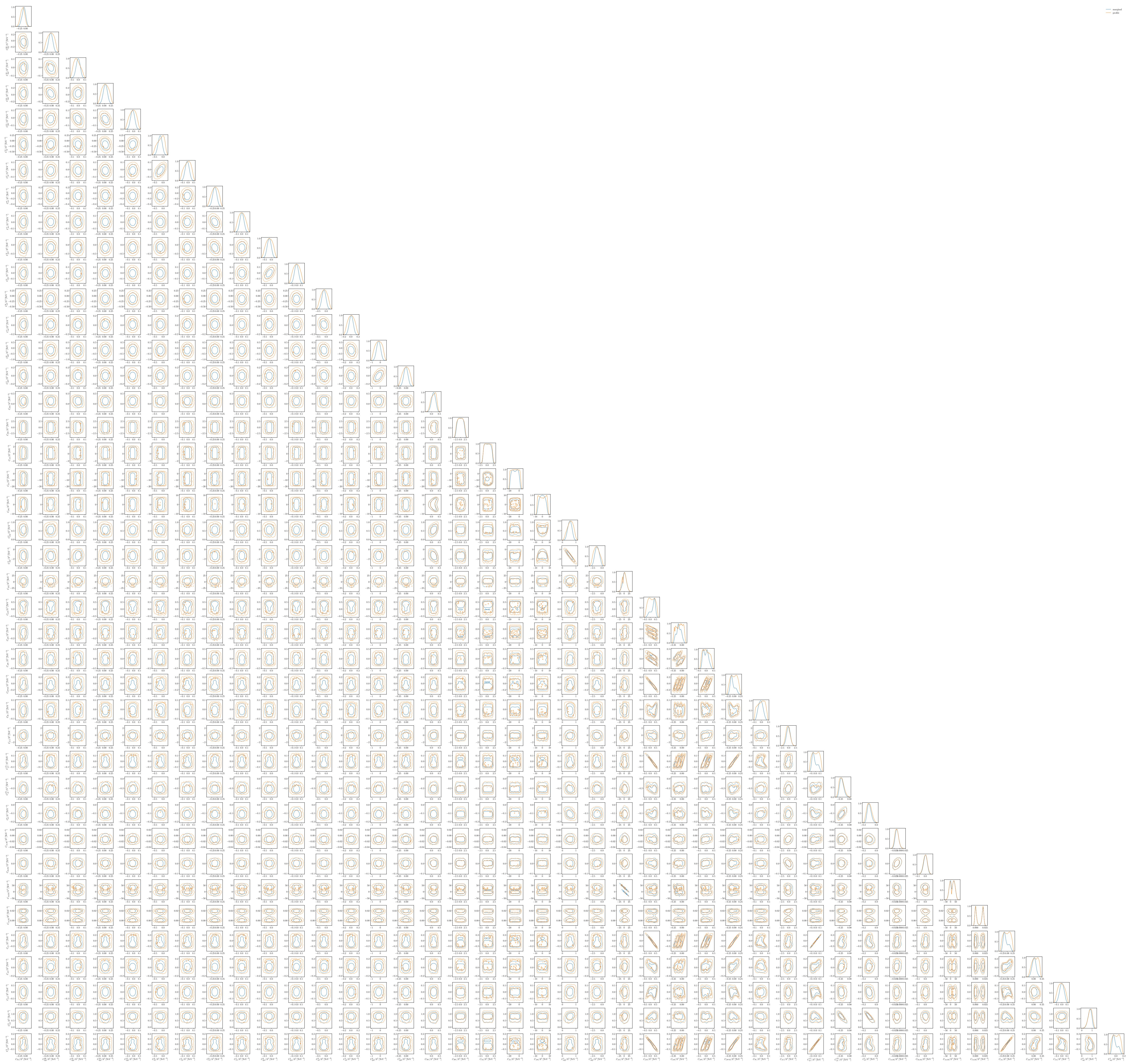

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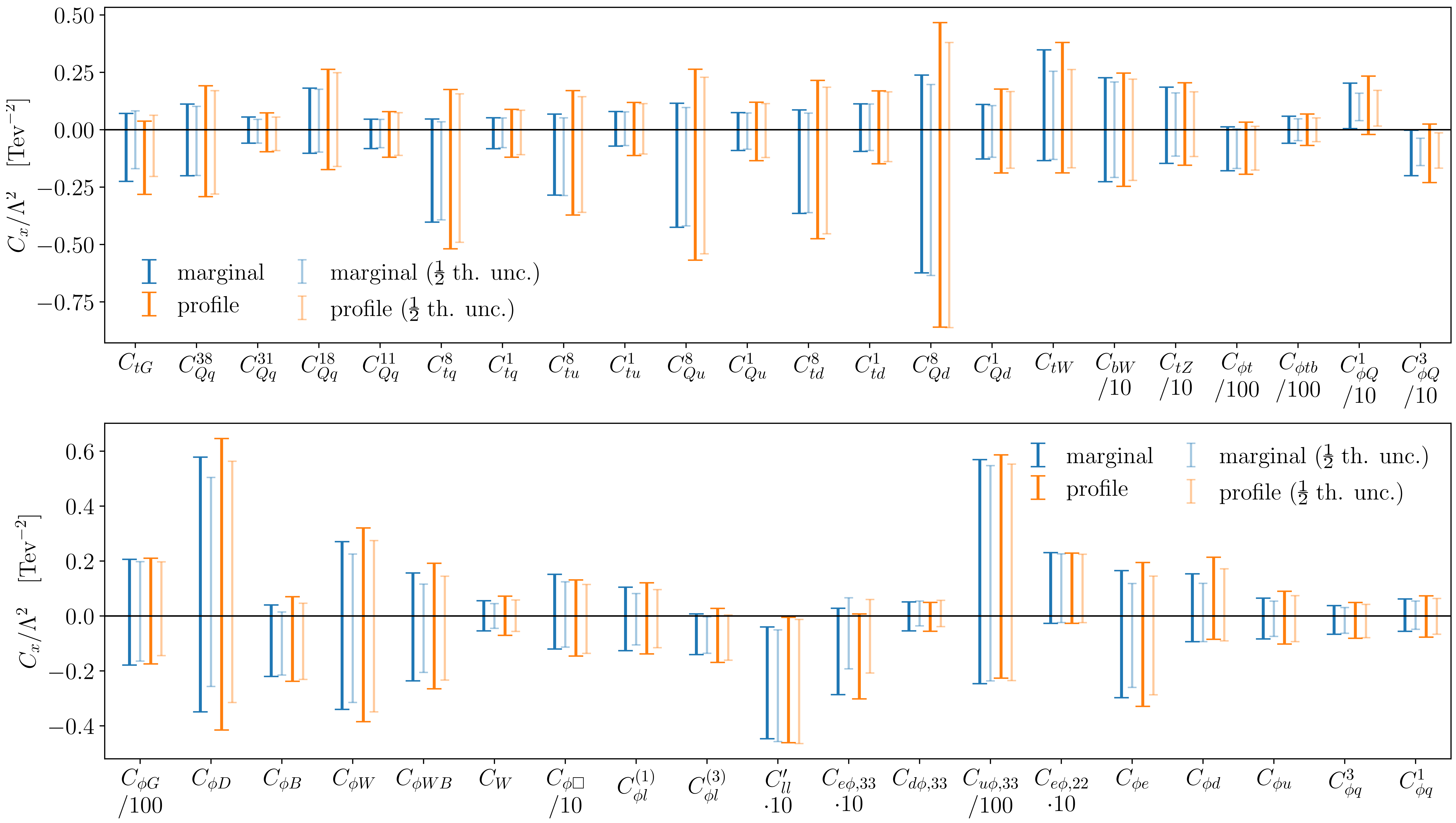
Final results



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

Summary

- NIS: powerful tool to **accelerate sampling**
- Significantly **improves sampling** of complex likelihoods while simultaneously providing **smoother** results
- The five steps to happiness can help fundamentally improve future SFITTER studies

Thank you, that’s it!

You should read the actual paper on

arXiv: 2411.00942

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

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 correlations

- Introduce **correlations** between same systematics

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

- We define $\chi^2_n = -2 \log \mathscr{L}_n$

Final SFITTER likelihood

$$-2 \log \mathscr{L} = \vec{\chi}^T C^{-1} \vec{\chi}$$