The MadNIS Reloaded

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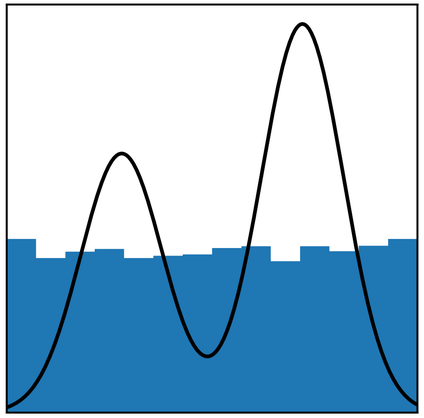
[2311.01548] TH, Huetsch, Maltoni, Mattelaer, Plehn, Winterhalder

Introduction

How can we make event generation faster?

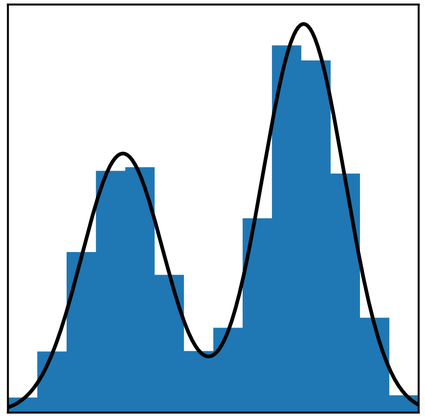
Efficient integration and sampling from differential cross section

$$\mathrm{d}\sigma = \frac{1}{\text{flux}} \mathrm{d}x_a \, \mathrm{d}x_b \, f(x_a) f(x_b) \, \mathrm{d}\Phi_n \left\langle \, |M_{\lambda,c,\ldots}(p_a, p_b \mid p_1, \ldots, p_n)|^2 \, \right\rangle$$



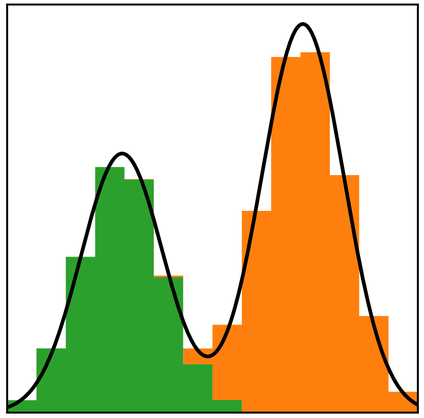
Flat sampling:
inefficient

$$I = \langle f(x) \rangle_{x \sim p(x)}$$



Importance sampling:
mapping close to integrand

$$I = \left\langle \frac{f(x)}{g(x)} \right\rangle_{x \sim g(x)}$$



Multi-channeling:
mapping for each channel

$$I = \sum_i \left\langle \alpha_i(x) \frac{f(x)}{g_i(x)} \right\rangle_{x \sim g_i(x)}$$

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Sum over channels

MadGraph: build channels from Feynman diagrams

Integrand

MadGraph: $\mathrm{d}\sigma/\mathrm{d}x$

$$I = \sum_i \left\langle \alpha_i(x) \frac{f(x)}{g_i(x)} \right\rangle_{x \sim g_i(x)}$$

Channel weights

MadGraph: $\alpha_i \sim |M_i|^2$

or $\alpha_i \sim \prod |p_k^2 - m_k^2 - \mathrm{i} M_k \Gamma_k|^{-2}$

Channel mappings

MadGraph: use propagators, …

Refine with VEGAS (factorized, histogram based importance sampling)

MadNIS: Neural Importance Sampling

$$I = \sum_i \left\langle \alpha_i(x) \frac{f(x)}{g_i(x)} \right\rangle_{x \sim g_i(x)}$$

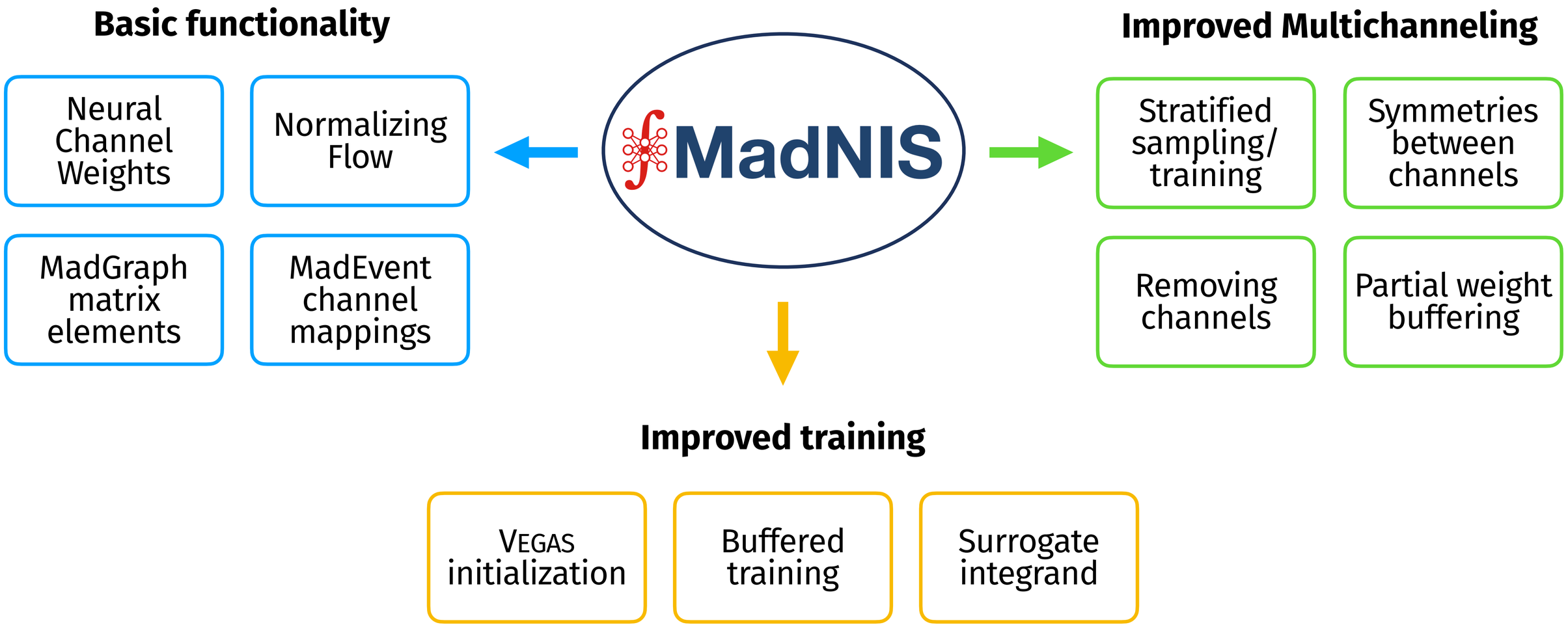
Use physics knowledge to construct channels and mappings

Normalizing Flow to refine channel mappings

Fully connected network to refine channel weights

Optimize simultaneously with integral variance as loss function

Overview


Basic functionality
Neural Channel Weights
Normalizing Flow
MadGraph matrix elements
MadEvent channel mappings
MadNIS
Improved Multichanneling
Stratified sampling/ training
Symmetries between channels
Removing channels
Partial weight buffering
Improved training
VEGAS initialization
Buffered training
Surrogate integrand

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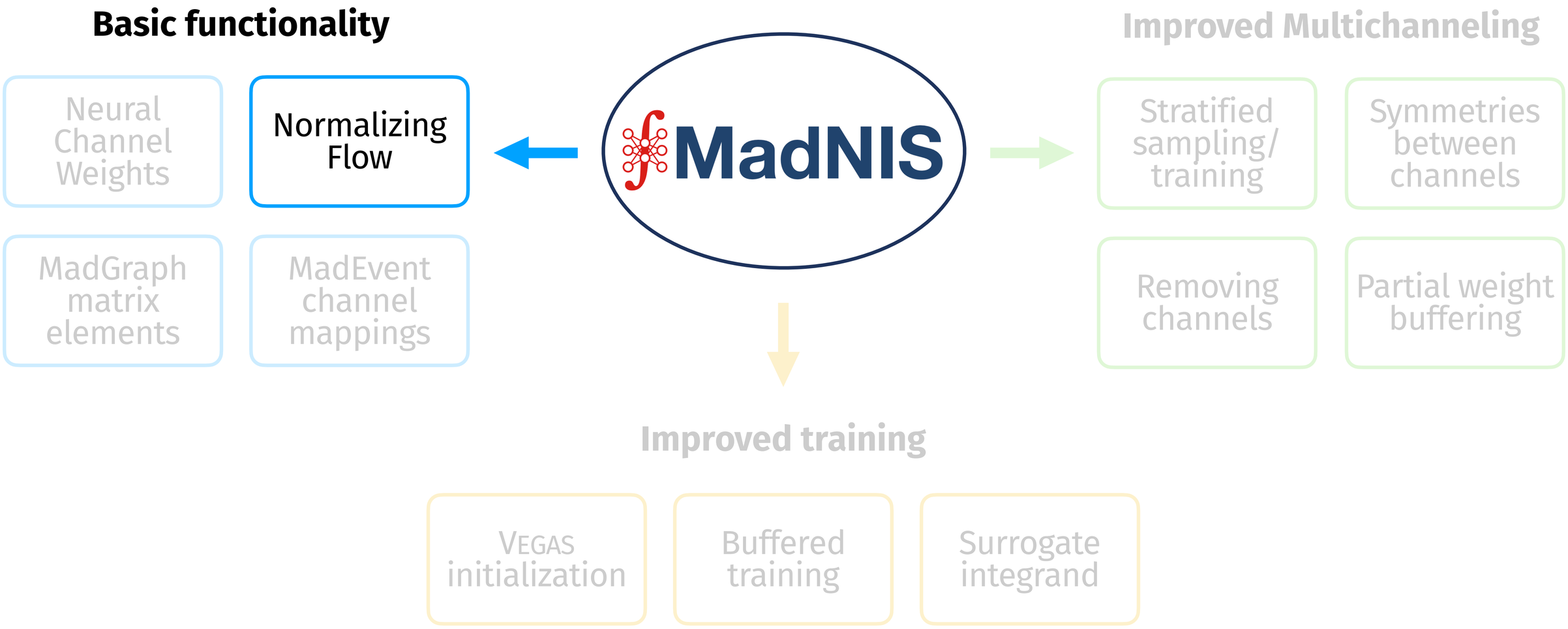
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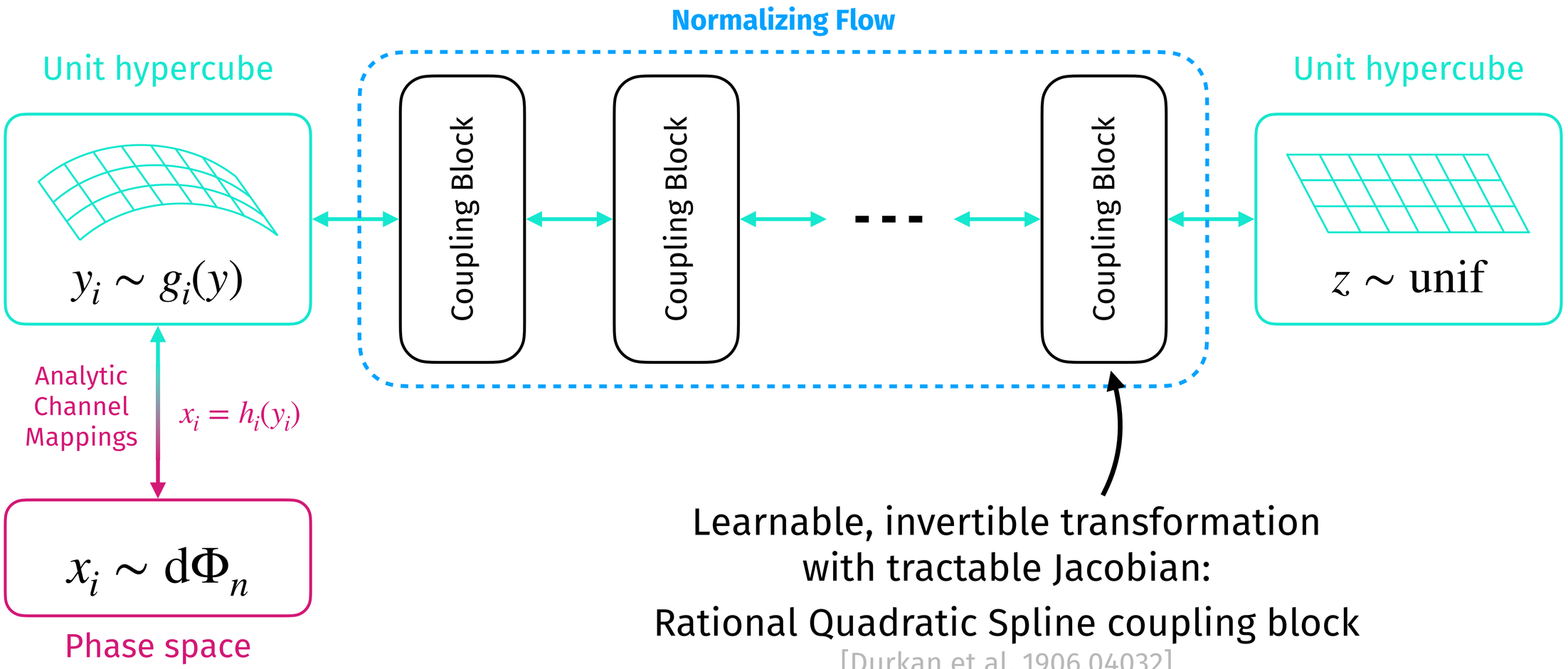
Neural Importance Sampling



Flows for NIS: [Gao et al, 2001.05486] [Gao et al, 2001.10028] [Bothmann et al, 2001.05478]

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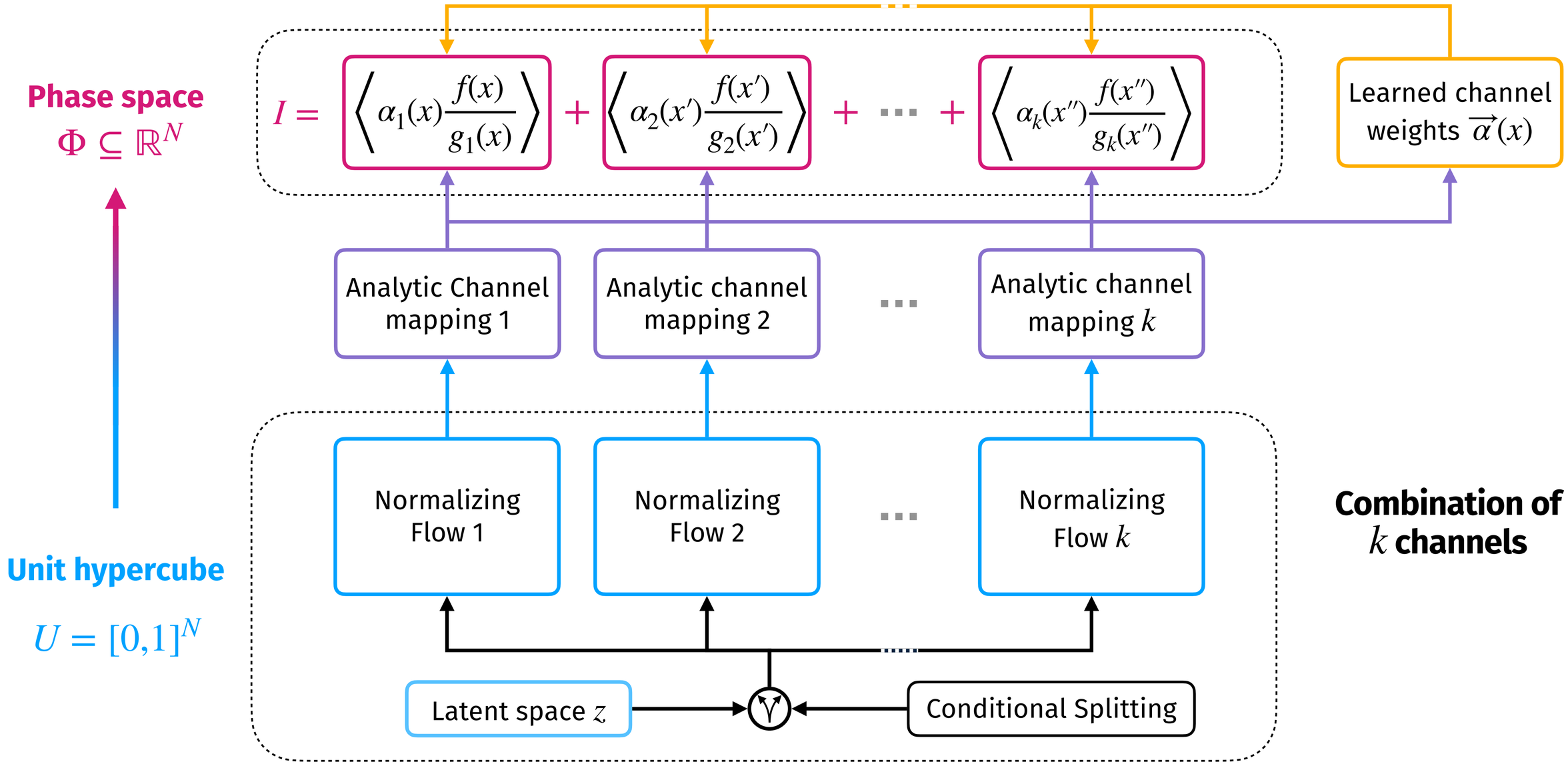
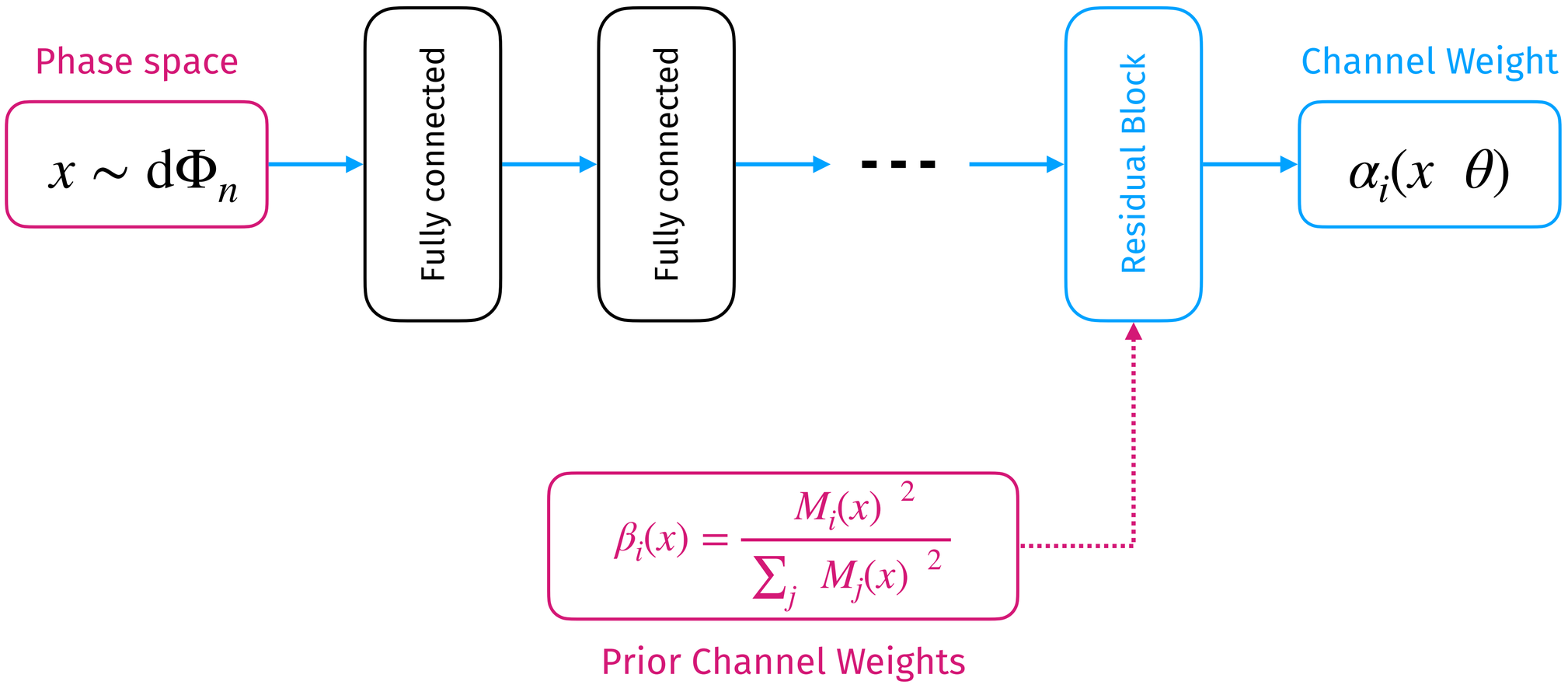


Neural Channel Weights



Loss function

Training objective:
Minimize total variance

$$\sigma_{\text{tot}}^2 = N \sum_i \frac{\sigma_i^2}{N_i} \qquad \text{with}$$

$$\sigma_i^2 = \text{Var}\left(\alpha_i(x) \frac{f(x)}{g_i(x)} \right)_{x \sim g_i(x)}$$

Optimal MC weights depend on N_i

↓

assume choice of N_i during training:
use stratified sampling

$$N_i = N \frac{\sigma_i}{\sum_k \sigma_k}$$

MadNIS loss function

$$\mathscr{L} = \sigma_{\text{tot}}^2 = \sum_{i,k} \sigma_i \, \sigma_k$$

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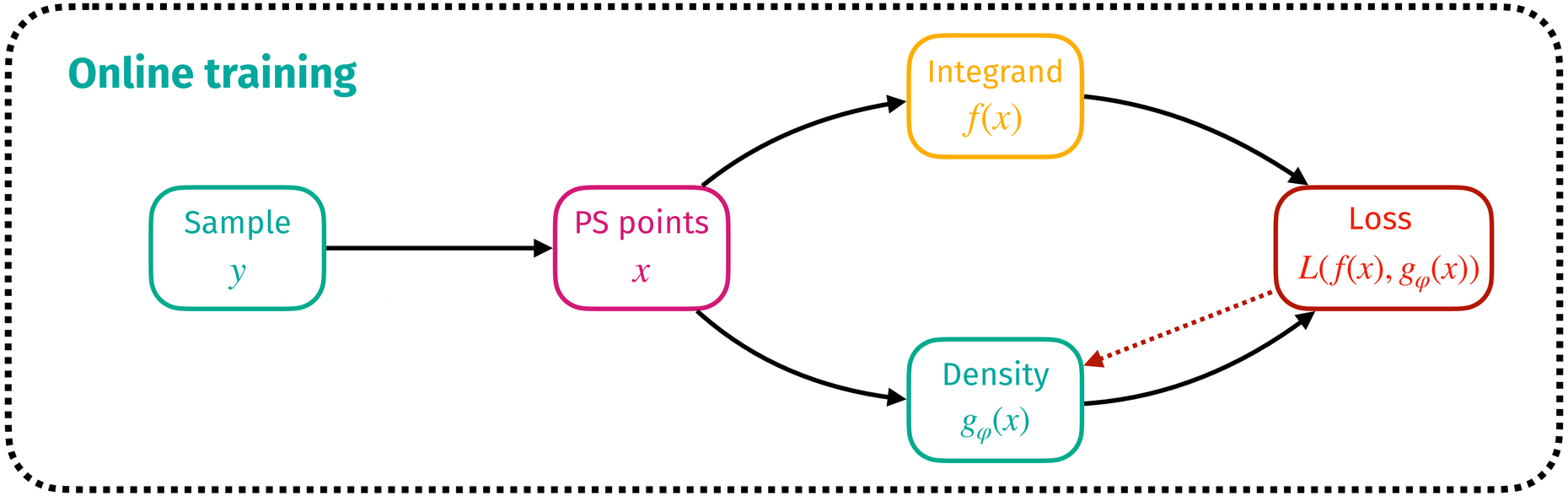

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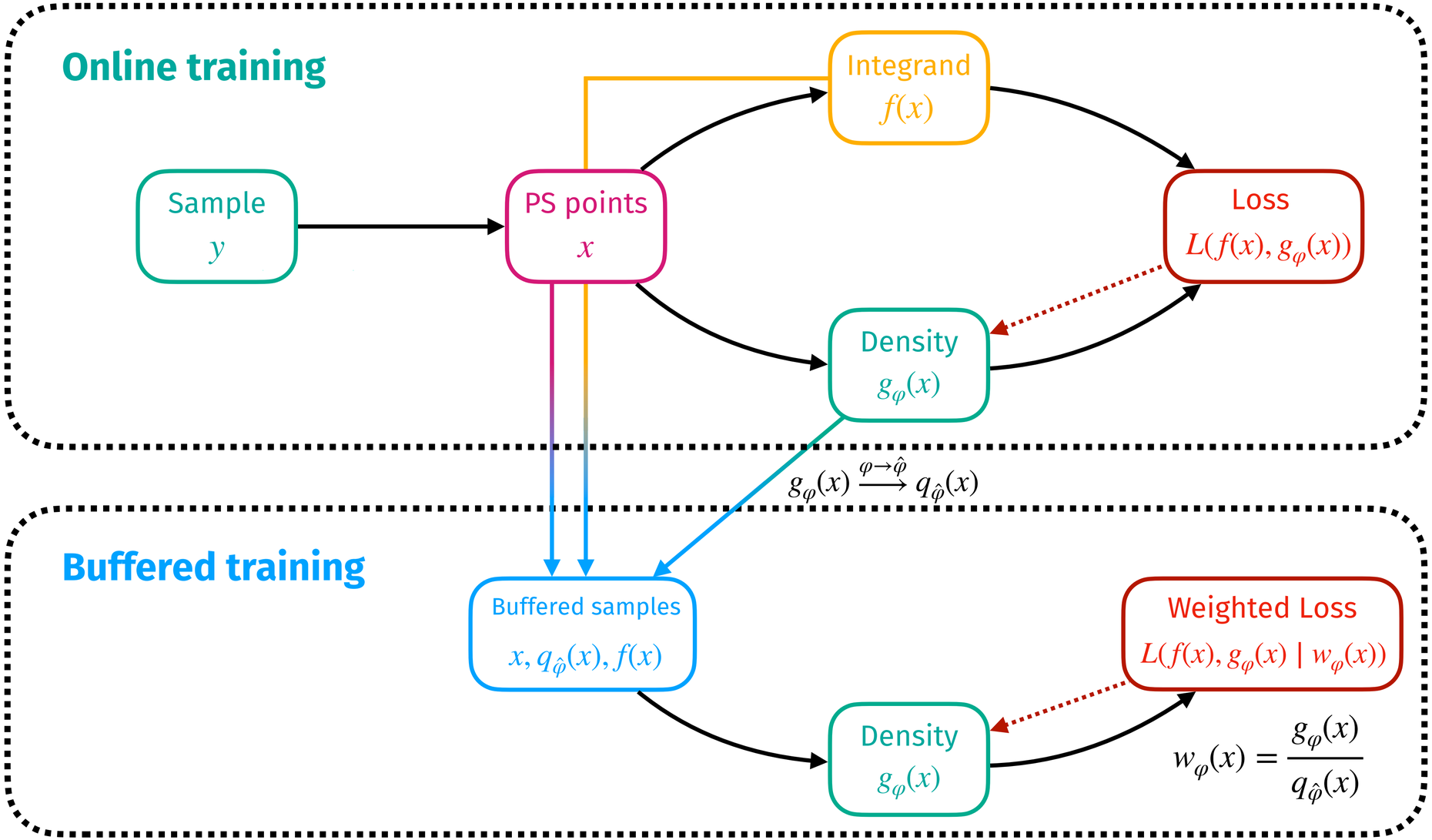

Buffered Training

Training algorithm

generate new samples, train on them, save samples

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train on saved samples n times

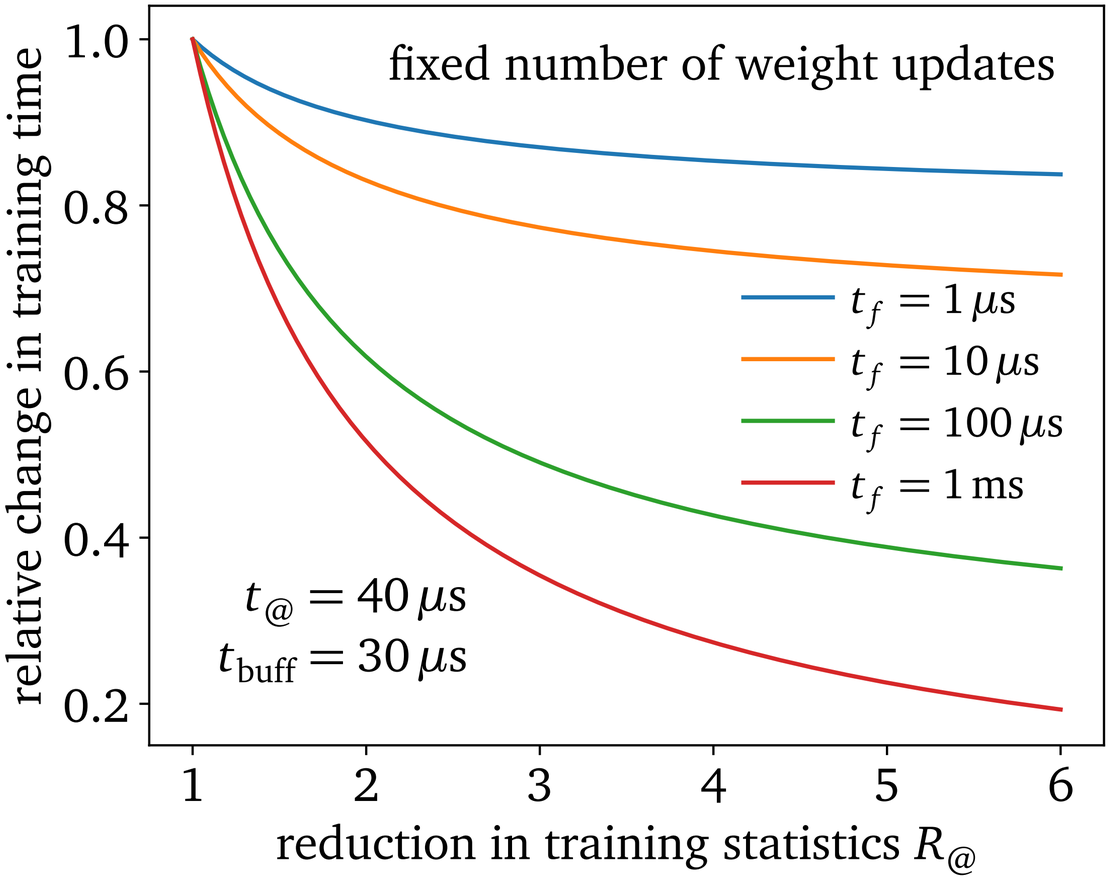
↓

repeat

↓

Reduction in training statistics by

$$R_{@} = n + 1$$



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VEGAS Initialization

	VEGAS	Flow
Training	Fast	Slow
Correlations	No	Yes

Combine advantages:

Pre-trained VEGAS grid as
starting point for flow training

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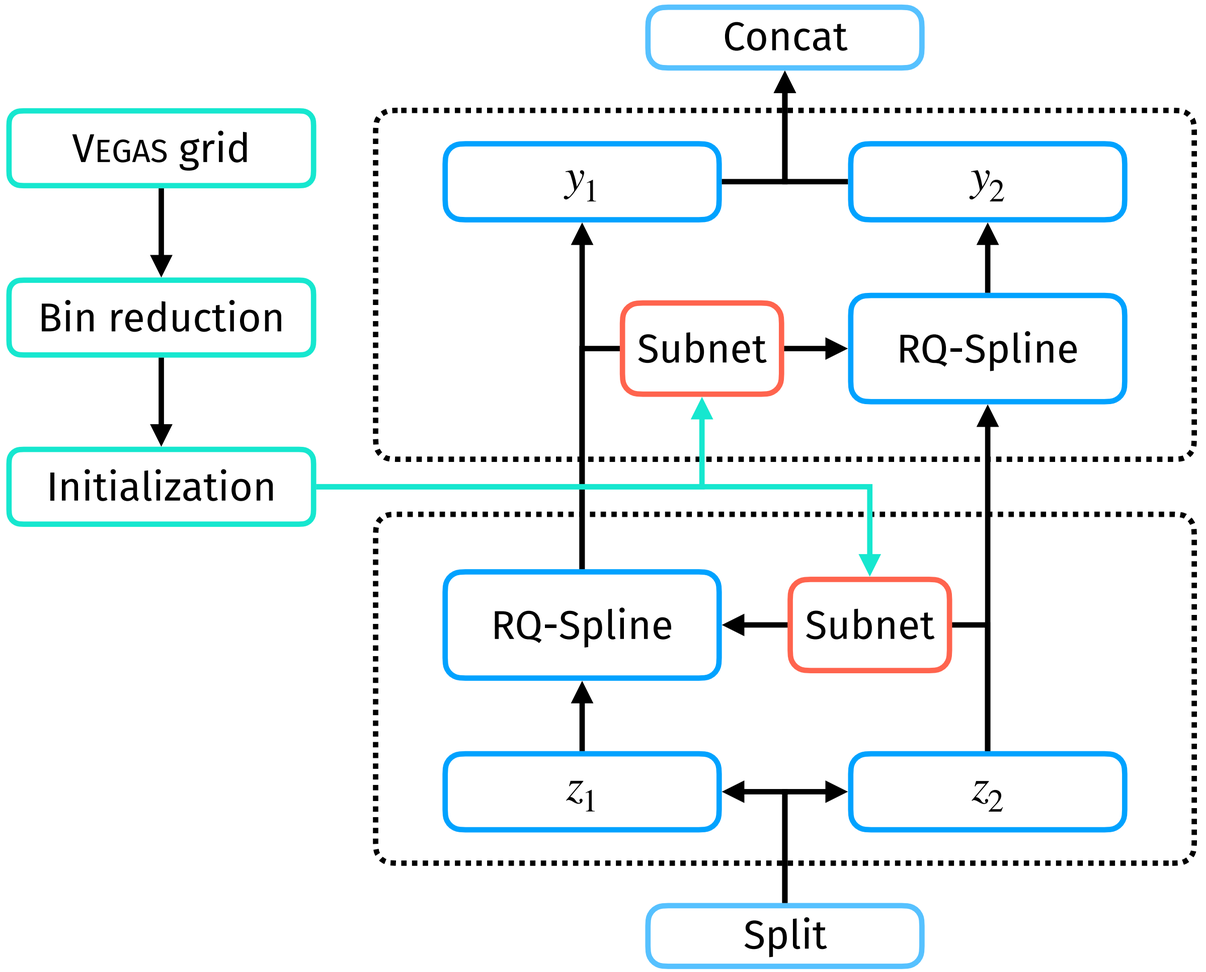

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Improved Multichanneling

Use symmetries

Groups of channels only **differ by permutations** of final state momenta

↓

use **common flows** and combine in loss function

Stratified training

Channels have different contributions to the total variance

↓

more samples for channels with **higher variance** during training

Channel dropping

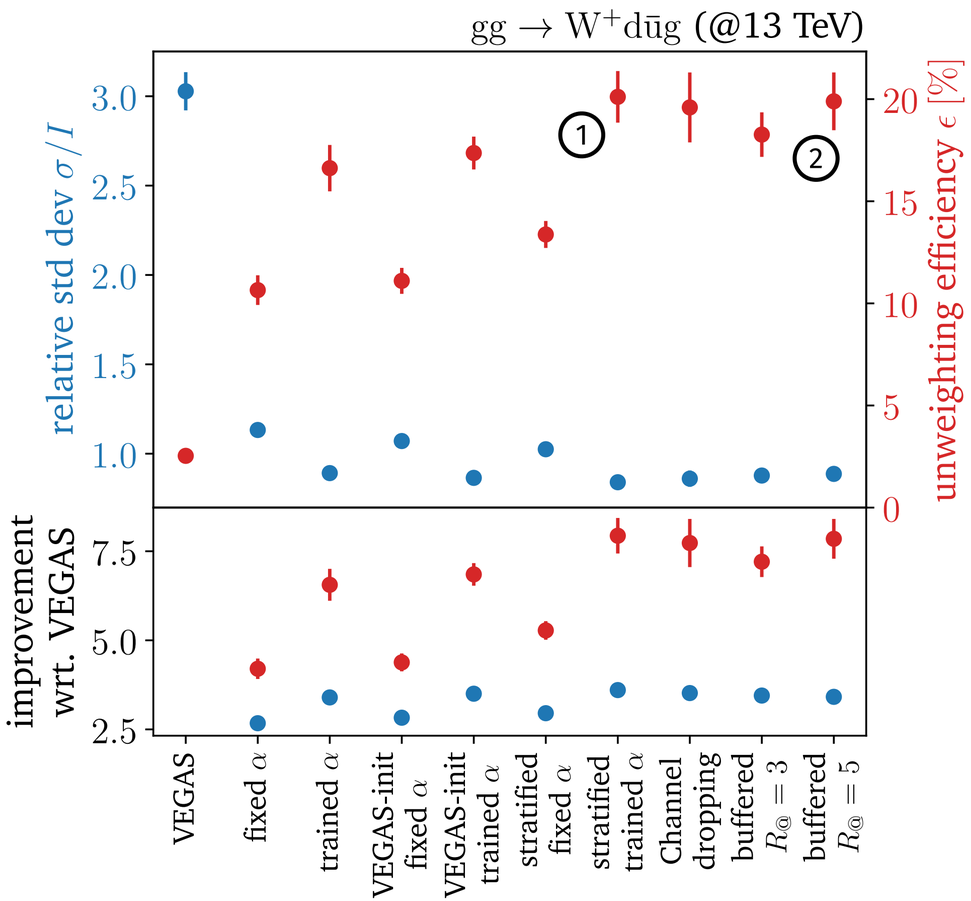
MadNIS often **reduces contribution** of some channels to total integral

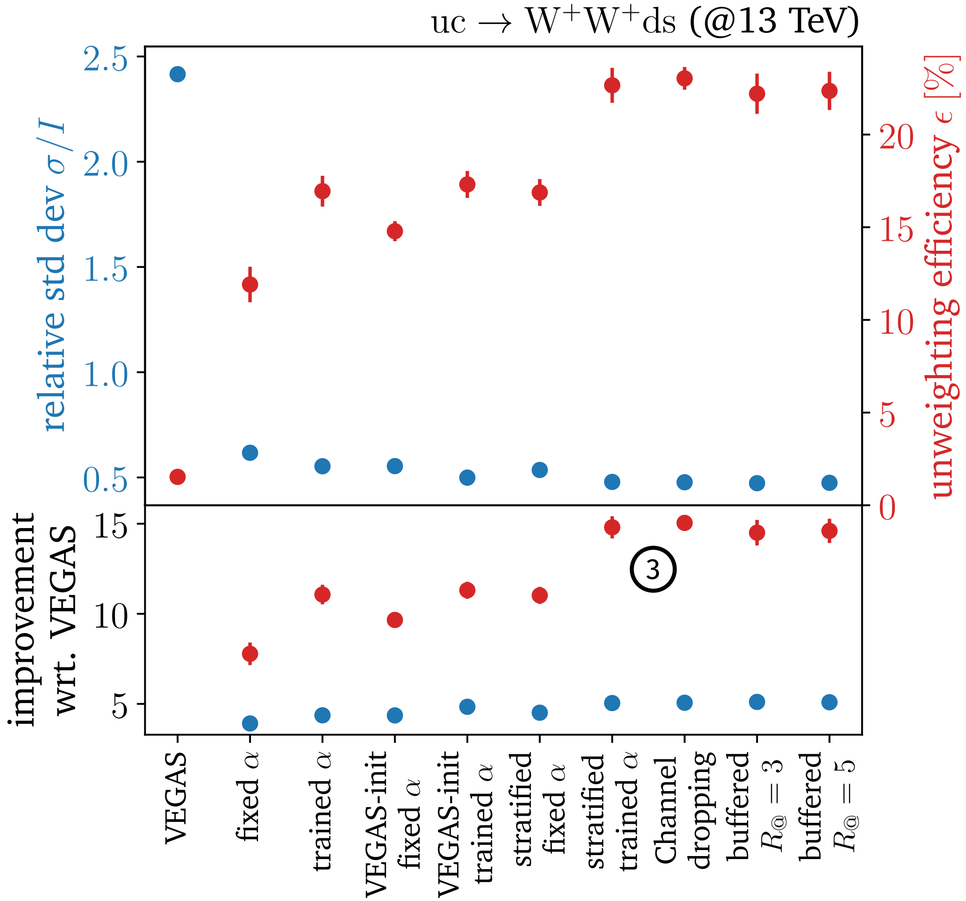
↓

remove insignificant channels from the training completely

Reduced complexity
Improved stability

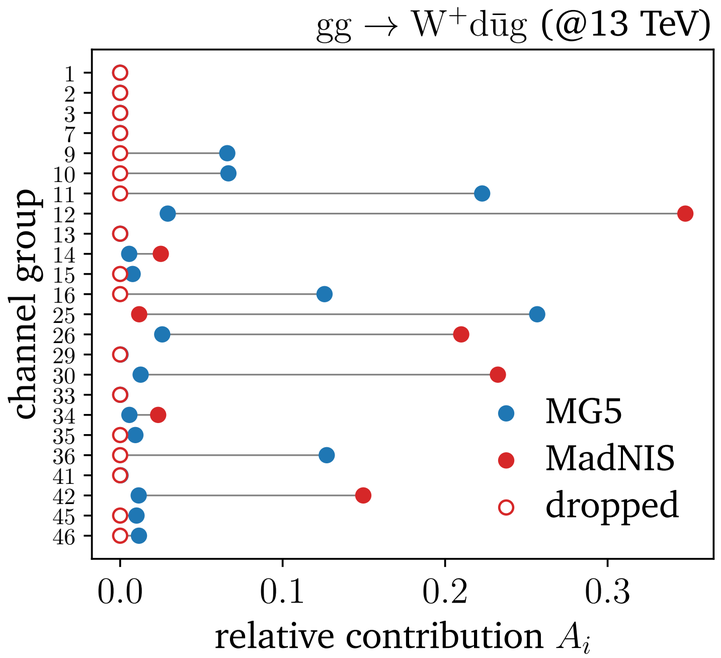
LHC processes

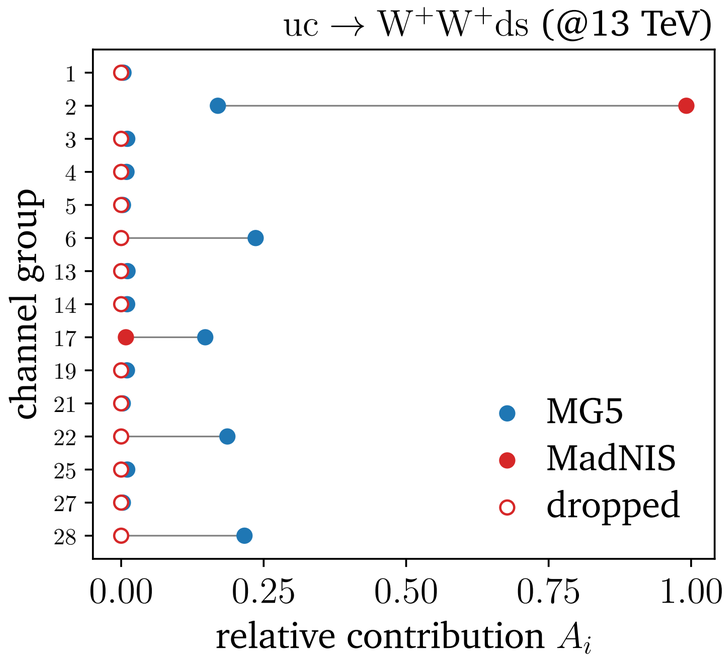




1. Excellent results by combining all improvements!
2. Same performance with buffered training
3. Even larger improvements for process with large interference terms

Learned channel weights



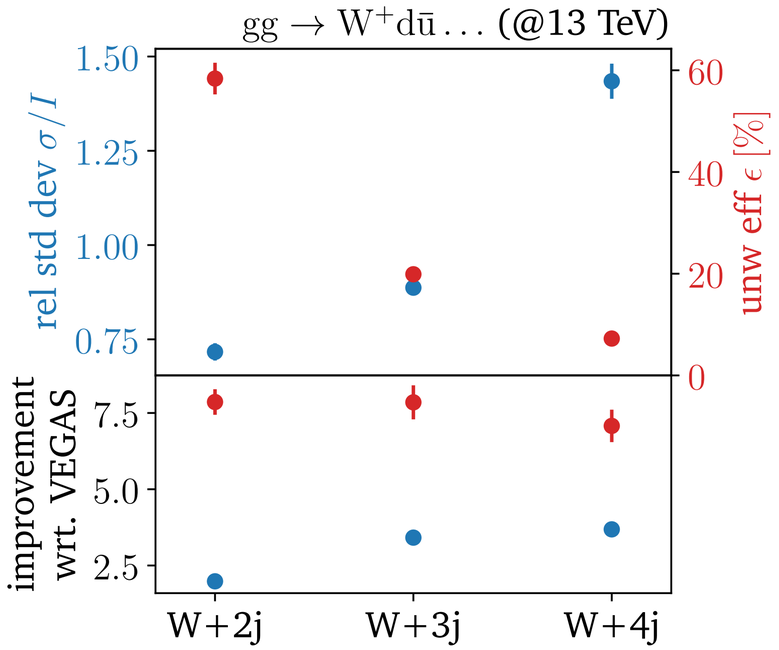


MadNIS often sends weight of many channels to 0

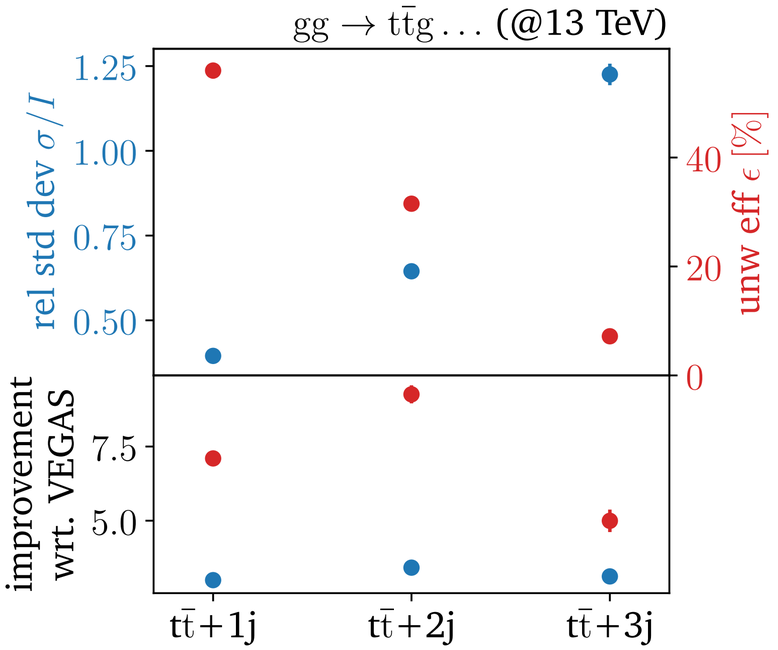
↓

dropping channels makes training and
event generation more stable and efficient

Scaling with multiplicity



$gg \to W^+d\bar{u}gg$
384 channels, 108 symm.
7x better than VEGAS



$gg \to t\bar{t}ggg$
945 channels, 119 symm.
5x better than VEGAS

Large improvements compared to VEGAS even
for high multiplicities and many channels!

Outlook

The MadNIS Reloaded

Large improvements,
even for high multiplicities
and complicated processes!

[2311.01548]

Future plans

Make MadNIS part of next
MadGraph version