

Unifying MadNIS and Amplitude Surrogates for NLO

Giovanni De Crescenzo, Javier Mariño Villadamigo, Nina Elmer, Theo Heimel,
Tilman Plehn, Ramon Winterhalder, and Marco Zaro

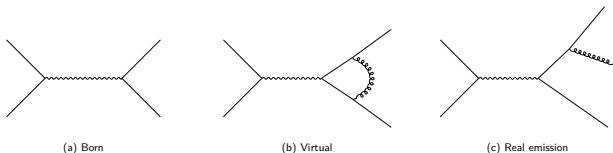
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Cross section at Next to Leading Order

Cross section at Next-to-Leading-Order (NLO) combines three contributions

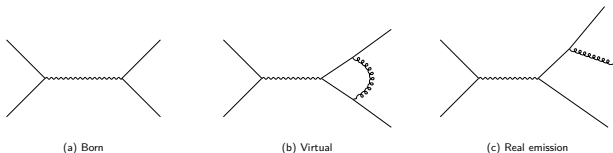


Virtual and real diagrams IR divergent; sum is finite (KLN theorem)

$$d\sigma^{\text{NLO}} = \underbrace{\int d\Phi_n \left[d\sigma^{\text{B}} + d\sigma^{\text{V}} \right]}_{n\text{-body}} + \underbrace{\int d\Phi_{n+1} d\sigma^{\text{R}}}_{(n+1)\text{-body}} \quad (1)$$

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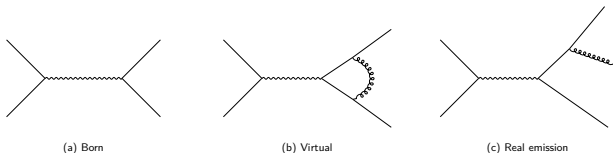


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Key point

Sum is finite but separate integrals are not; possible to implement analytical cancellation in numerical methods

FKS subtraction scheme

Store the cancellation in real part of $d\sigma$.

$$d\sigma^R \rightarrow \sum_{ij \in \text{sectors}} d\sigma_{ij}^R \propto |\mathcal{M}|^2 \mathcal{S}_{ij} \xi_i^2 (1 - y_{ij}) = \Sigma_{ij} \quad (2)$$

$\mathcal{S}_{ij}$: sector partition function

ξ_i : energy of emitted gluon

y_{ij} : collinearity of sector pair

Implicitly we translate the integration into the following numerical integral (well behaved):

$$d\sigma^R \rightarrow \sum_{ij} \int_{d\Phi_n} d\xi_i dy_{ij} \frac{\Sigma_{ij} - \overbrace{\Sigma_{ij}(\text{sing.})}^{\text{pole subtraction}}}{\underbrace{\xi_i(1 - y_{ij})}_{\text{regularization terms}}}$$

numerically hard:
0/0 if not careful!

Takeaway

FKS method: phase space partitioning, singular region regularization

Full subtracted term

$$\begin{aligned} d\sigma_{ij}^R - d\sigma_{ij}^S \propto \frac{1}{\xi_i^2(1 - y_{ij})} & \left[\Sigma_{ij}(\Phi_n, \xi_i, y_{ij}, \varphi_i) \right. \\ & - \Sigma_{ij}(\Phi_n, \xi_i, 1, \varphi_i) \Theta(y_{ij} - 1 + \delta) \\ & - \Sigma_{ij}(\Phi_n, 0, y_{ij}, \varphi_i) \Theta(\xi_{\text{cut}} - \xi_i) \\ & \left. + \Sigma_{ij}(\Phi_n, 0, 1, \varphi_i) \Theta(y_{ij} - 1 + \delta) \Theta(\xi_{\text{cut}} - \xi_i) \right]. \quad (3) \end{aligned}$$

- Subtraction of the *regularized* object Σ_{ij}
- Construction of different kinematics for subtraction terms

Full subtracted term

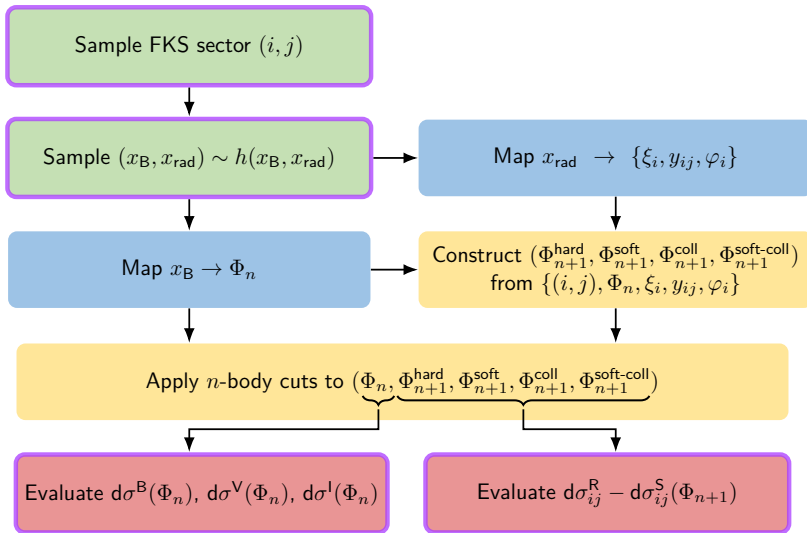
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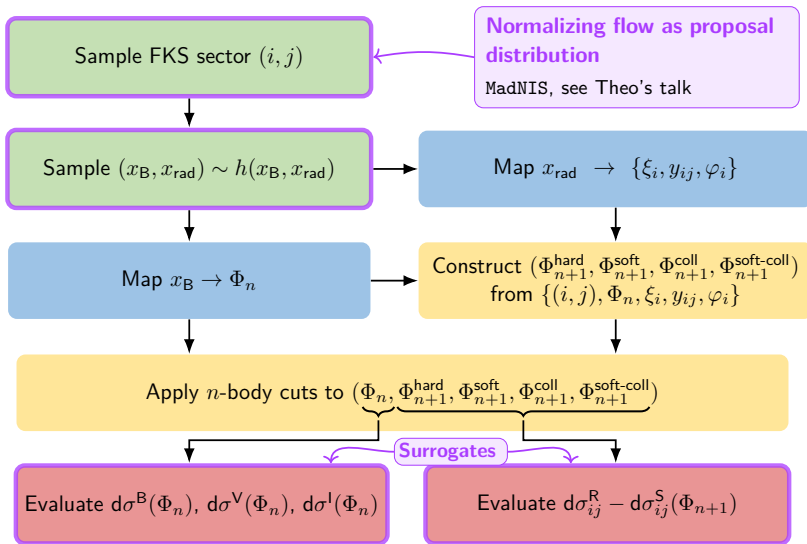
Cut hyperparameters

Cross section independent of δ , ξ_{cut} : hyperparameters to be optimized

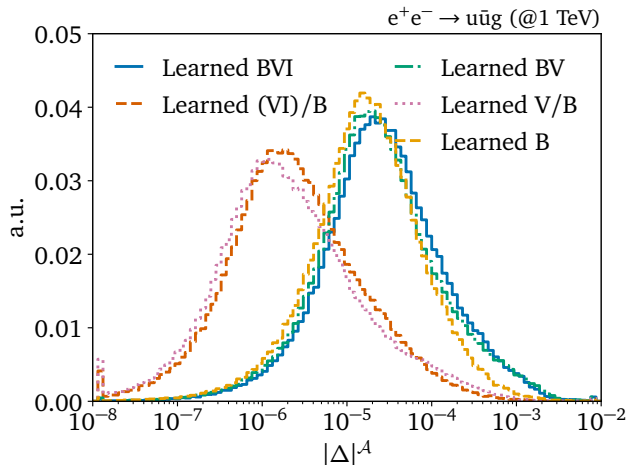
Sampling algorithm for MC integration



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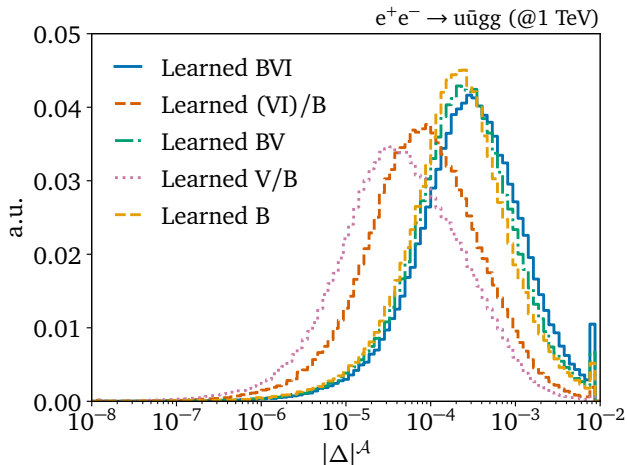


MLP results: virtual surrogate



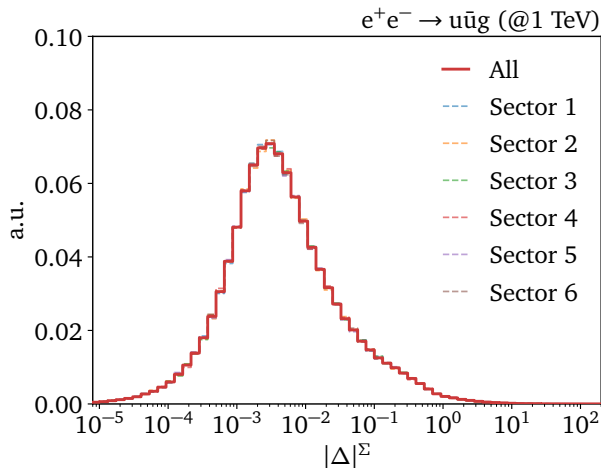
- Simple MLP; input are Φ_n and $\log s_{ij}$
- $|\Delta| = \left| \frac{\text{true} - \text{pred}}{\text{true}} \right|$
- Different target parameterization: $\frac{V}{B}$ easiest to learn

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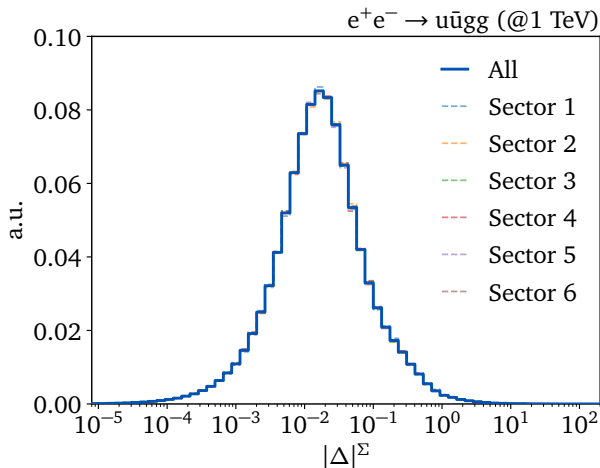
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MLP results: real surrogate



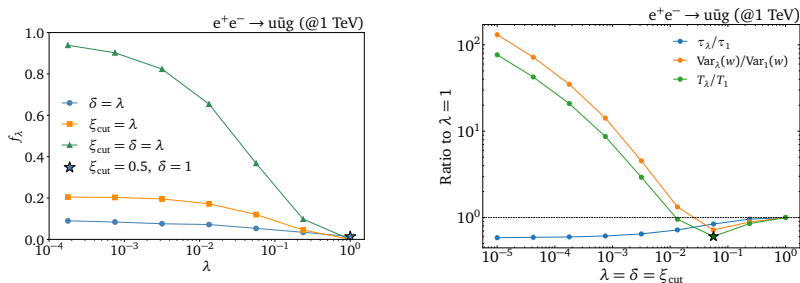
- Simple MLP; input are Φ_n , $\ln\text{-log } s_{ij}$ and radiation var.s
- Same metrics as before
- Worse performance overall
→ real test comes in integration

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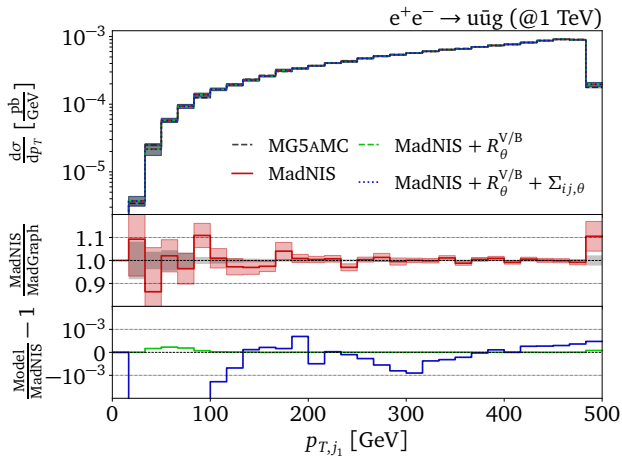
Optimizing the subtraction threshold



Fraction of surrogate calls f_λ (left) and evaluation-time/variance figure of merit (right) vs subtraction threshold λ .

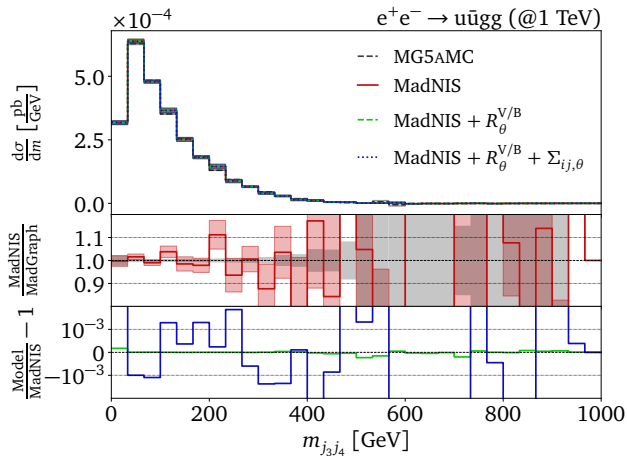
- Smaller λ : less subtraction support $\rightarrow$ more surrogate calls, but larger integrand variance
- Minimize total evaluation time $T_\lambda(\varepsilon)$ at fixed precision ε
- Optimum: $\lambda \approx 0.05$ ($f_\lambda \approx 40\%$) for 3-jet, $\lambda \approx 0.01$ ($f_\lambda \approx 65\%$) for 4-jet

MLP in integration: observable plots



- Errors with virtual surrogate within relative 10^{-3}
- Real surrogate (only inactive subtraction) maintain precision
- Consistent with VEGAS (MadGraph line for reference)

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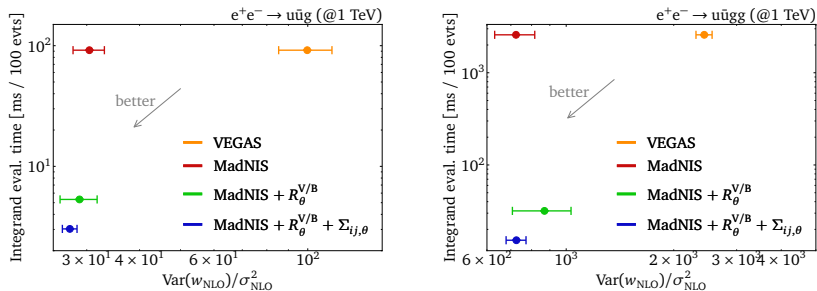
Cross sections: VEGAS vs MadNIS (+ surrogates)

Sampling mode	Surrogates		$e^+e^- \rightarrow u\bar{u}g$		$e^+e^- \rightarrow u\bar{u}gg$	
	$R_\theta^{V/B}$	$\Sigma_{ij,\theta}$	σ_{NLO} [pb]	$\text{Var}(w_{\text{NLO}})/\sigma_{\text{NLO}}^2$	σ_{NLO} [pb]	$\text{Var}(w_{\text{NLO}})/\sigma_{\text{NLO}}^2$
VEGAS	✗	✗	0.107 50(34)	100(14)	0.087 69(27)	2400(130)
MadNIS	✗	✗	0.107 60(19)	30.4(26)	0.087 29(15)	720(90)
MadNIS	✓	✗	0.107 59(18)	28.8(29)	0.087 11(18)	870(160)
MadNIS	✓	✓	0.107 65(18)	27.4(11)	0.087 38(15)	730(50)

Cross section and relative variance for each sampling/surrogate setup (mean $\pm$ std. dev. over 5 runs).

- Excellent agreement in σ_{NLO} across all setups
- Need 3–4 $\times$ more phase-space points with VEGAS to reach MadNIS precision

Acceleration: timing vs relative variance



Evaluation time vs relative variance: e⁺e⁻ → uūg (left), e⁺e⁻ → uūgg (right).

- MadNIS and VEGAS with actual amplitudes: same evaluation time, but 3× smaller RV
- Combined speed-up at fixed precision: ~110× (3-jet), ~570× (4-jet)

Outlook

- MadNIS works for NLO runs too
- Surrogates are precise enough to guarantee compatibility with true matrix element integration
- Possible next steps:
 - Higher final state multiplicities
 - Move to pp collisions
 - Extend real surrogates usage

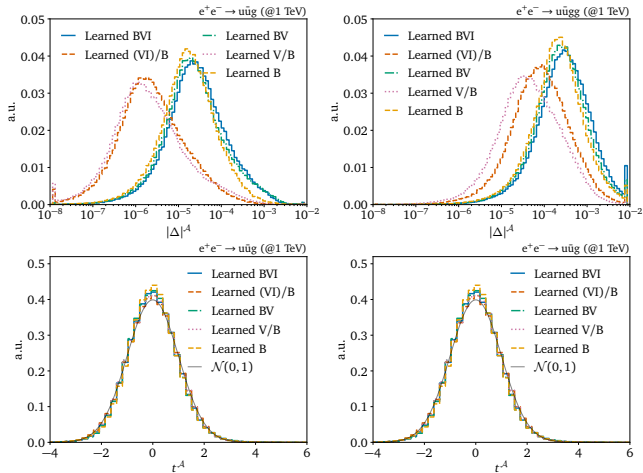
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Thank you for your attention!

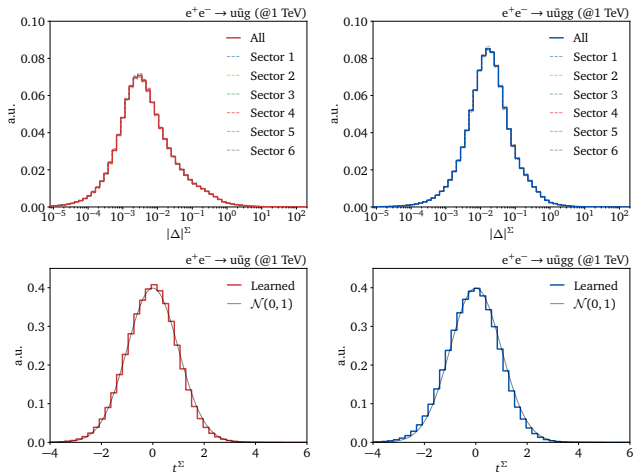
Backup

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Further histograms

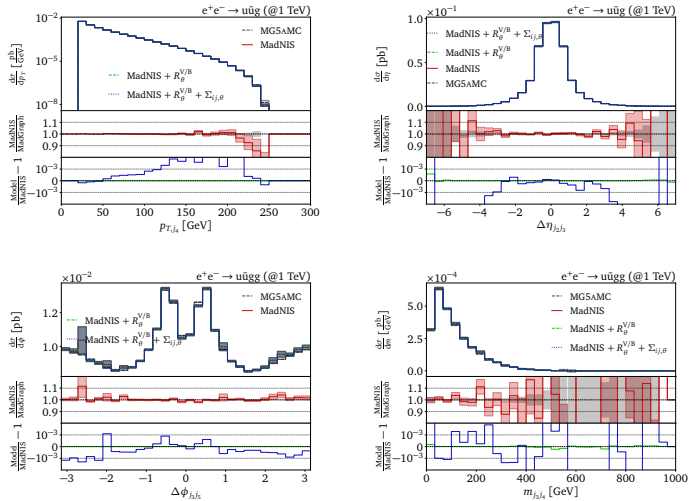


Figure: Additional observables: $e^+e^- \rightarrow u\bar{u}g$ (top), $e^+e^- \rightarrow u\bar{u}gg$ (bottom).