

# Negative weight

## workshop summary

Yannick Ulrich  
(he/him)

U Liverpool

Reminder: what are neg. weight & why do we care?

Event generators may produce events with  $w_i < 0$  b/c

- pert. exactness  $\rightarrow \text{Sola} \equiv \sigma_{\text{no}}$  often involves  $\overline{CT}$   
 $\rightarrow w < 0$

- in showers, if shower overestimates Real matrix element,  $w_i < 0$  to counter that

Why is this a problem?

If  $r \propto N$  out of  $N$  events are neg., statistics needs increase by  $\frac{1}{(1-2r)^2}$

solutions: - (any of the following)

- fast simulations

# KrkNLO (James Whitehead)

finite part of PDF renorm. has scheme dependence @ NLO and beyond  
→ change this to avoid negative weights

$$w \rightarrow w \left[ 1 + \frac{\alpha}{\Gamma} \left( \frac{V}{B} + \frac{I}{B} + \Delta^{\text{FS}} \right) \right]$$

↑ large enough

## KrkNLO

Key ideas:

### KrkNLO matching for colour-singlet processes

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**ABSTRACT:** Matched calculations combining perturbative QCD with parton showers are an indispensable tool for LHC physics. Two methods for NLO matching are in widespread use: MC@NLO and POWHEG. We describe an alternative, KrkNLO, reformulated to be easily applicable to any colour-singlet process. The primary distinguishing characteristic of KrkNLO is its use of an alternative factorisation scheme, the ‘Krk’ scheme, to achieve NLO accuracy. We describe the general implementation of KrkNLO in Herwig 7, using diphoton production as a test process. We systematically compare its predictions to those produced by MC@NLO with several different choices of shower scale, both truncated to one-emission and with the shower running to completion, and to ATLAS data from LHC Run 2.

**KEYWORDS:** Higher-Order Perturbative Calculations, Parton Shower

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- change PDF factorisation scheme (‘Krk’ scheme: exploit ambiguity!)
- matching becomes multiplicative
- no subtraction: weights all positive

based on work with Staszek Jadach, Andrzej Siódmok, Pratixan Sarmah

# ESME in Pan Scales (Alex Karlberg)

idea: can't avoid negative weights & discarding changes N<sup>LO</sup> exactness

→ push problem to N<sup>NLO</sup>

CERN

## A Sudakov algorithm

We want to transform the problem, such that we are guaranteed that negative weights are only associated with terms beyond  $\mathcal{O}(\alpha_s)$ .

### Exponentiated subtraction

- Start with normalisation  $n_B = 1$  and the max value for  $k_t$  (ordering variable)  
Run a loop while  $k_t > k_{t,\min}$ :
  - Sample  $\ln k_t$  from  $e^{-M/B_0 \ln 1/k_t}$ , where  $M = \max(R, C)$ ,
  - generate random number  $0 < r < 1$
  - if  $r < \frac{|R-C|}{M}$  then
    - if  $R > C$ :  $n_B \rightarrow n_B + 1$
    - if  $C > R$ :  $n_B \rightarrow n_B - 1$
- return  $n_B$

↖ only addresses problems of over estimate

$$\langle n_b \rangle = 1 + \int [R(\Phi) - C(\Phi)] / B_0 d\Phi_{\text{rad}}$$



ARCANE (Prasanth Shyamsundar)

define  $\bar{F}(V) = \int dL F(V, L) > 0$  but  $F(V, L) \not> 0$   
obs. property  $\nearrow$   $\nwarrow$  latent property eg. history

## ARCANE reweighting

- Under ARCANE reweighting, the density of  $(V, L)$  is modified as:

$$F^{(\text{arcane})}(V, L) = F(V, L) + G(V, L)$$

where  $G$  satisfies  $\int dL G(V, L) = 0$ .

- This way  $F^{(\text{arcane})}(V) \stackrel{\text{exactly}}{=} F(V)$ .
- $G$  redistributes the contributions of different  $(V, L)$ -s to the same  $V$ , to try and get  $F^{(\text{arcane})}(V, L)$  to have the same sign as  $F(V)$ .

### Two questions:

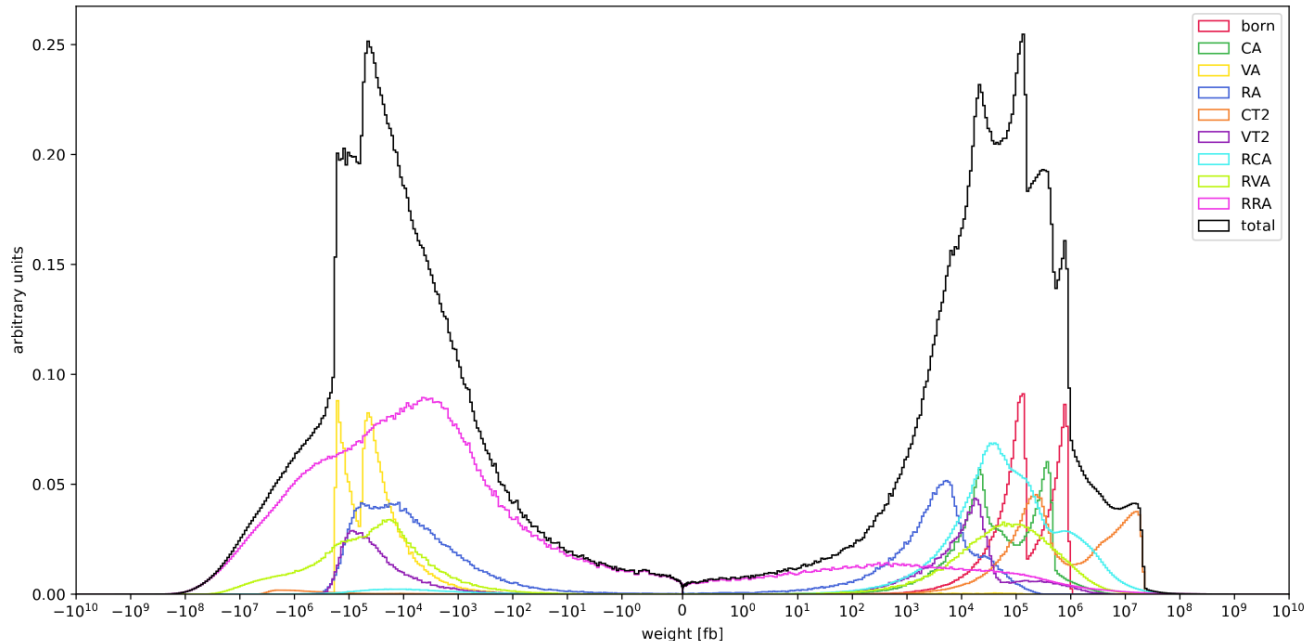
cmp. redistr.  
across history

- 1) How does one construct the redistribution function  $G$ ?
- 2) How does one sample events from  $F^{(\text{arcane})}(V, L)$ .

# MATRIX event generation (Oleksandr Zenaiev)

PDF fits  $\leadsto$  event generation with MATRIX for  $pp \rightarrow t\bar{t}$

## $t\bar{t}$ @ NNLO in MATRIX: weights

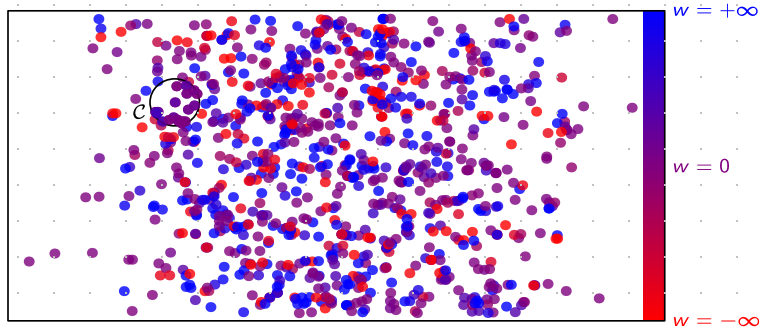


- Largest (positive and negative) weights: RRA  $gg \rightarrow t\bar{t}gg$  and CT2  $gg \rightarrow t\bar{t}$
- These are most time consuming contributions (also RVA  $gg \rightarrow t\bar{t}g$  which is slow itself)

Cell resampling: a strategy to remove neg weights  
(Andrew Maier)

## Cell Resampling

[Andersen, Gütschow, Maier, Prestel 2020; Andersen, Maier 2021]



Cell resampling:

- 1 Choose seed event with negative weight for cell  $\mathcal{C}$
- 2 Iteratively add nearest event to cell until  $\sum_{i \in \mathcal{C}} w_i \geq 0$  or radius exceeds  $r_{\max}$
- 3 Redistribute weights, e. g. average over cell:  $w_i \rightarrow w = \frac{\sum_j c w_j}{\# \text{ events in } \mathcal{C}}$
- 4 Repeat

... in QED using McMule (1/4)

$r \times N$  events have  $w < 0$



Note  $\alpha_{\text{QED}} \ll \alpha_s \Rightarrow$  need many more events

| Order | $\xi_c$ | $N$   | $r$  | $[w_{\min}, w_{\max}]/\langle w \rangle$ | feature      |
|-------|---------|-------|------|------------------------------------------|--------------|
| LO    | n/a     | 99.7M | 0.0% | $[0.03, 7.7]$                            |              |
| NLO   | 0.1     | 220M  | 0.5% | $[-3.6, 3.6] \times 10^7$                | cres<br>subs |
|       |         | 51M   | 0.1% | $[-1.3, 19] \times 10^3$                 |              |
|       | 1.0     | 216M  | 0    | $[+0.0, 1.6] \times 10^4$                | cres<br>subs |
|       |         | 61M   | 3.5% | $[-2.1, 2.1] \times 10^6$                |              |
| NNLO  | 0.1     | 21.1G | 0.3% | $[-7.0, 26] \times 10^3$                 | cres         |
|       |         | 3.6G  | 0    | $[+0.0, 2.5] \times 10^4$                |              |
|       | 1.0     | 19.8G | 0.7% | $[-8.6, 8.6] \times 10^7$                | cres         |
|       |         | 1.2G  | 0.1% | $[-6.9, 6.9] \times 10^5$                |              |
|       |         |       | 9.2% | $[-2.3, 2.3] \times 10^8$                |              |
|       |         |       | 0.5% | $[-3.3, 2.4] \times 10^4$                |              |

Significant  
reduction  
in  $r$



non-pos. integrands with normalising flow  
(Rene Poncelet)

treat pos. & neg. part separately for generation by learning them

## Stratification of signed integrands

There are ways around:

1) Add a large constant

2) Stratification:  $f(\mathbf{x}) = f_+(\mathbf{x}) + f_-(\mathbf{x})$ , with  $f_{\pm}(\mathbf{x}) = \Theta(\pm f(\mathbf{x}))f(\mathbf{x})$

learn those in two networks

→ 
$$I = \int_{\mathbf{H}_+(\mathbf{x}) \in \Omega} d\mathbf{H}_+ \frac{f_+(\mathbf{x})}{h_+(\mathbf{x})} + \int_{\mathbf{H}_-(\mathbf{x}) \in \Omega} d\mathbf{H}_- \frac{f_-(\mathbf{x})}{h_-(\mathbf{x})}$$
 "two independent integrals"

$$\hat{I}_{\text{strat}} = \hat{I}_+ + \hat{I}_- = \frac{1}{N_+} \sum_{i=1}^{N_+} \frac{f_+(\mathbf{x}_i)}{h_+(\mathbf{x}_i)} + \frac{1}{N_-} \sum_{i=1}^{N_-} \frac{f_-(\mathbf{x}_i)}{h_-(\mathbf{x}_i)}$$

$$\delta \hat{I}_{\text{strat}} = \sqrt{\frac{1}{N-1} \left[ \frac{N}{N_+} \text{Var}(\hat{I}_+) + \frac{N}{N_-} \text{Var}(\hat{I}_-) \right]}$$
$$\text{Var}(\hat{I}_{\pm}) = \frac{1}{N_{\pm}} \sum_{i=1}^{N_{\pm}} \left( \frac{f_{\pm}(\mathbf{x}_i)}{h_{\pm}(\mathbf{x}_i)} \right)^2 - \hat{I}_{\pm}^2$$

- + The total variance is now bounded by the individual variances
- The mappings are more complicated (need high phase space efficiency)

this is where normalising flow comes in

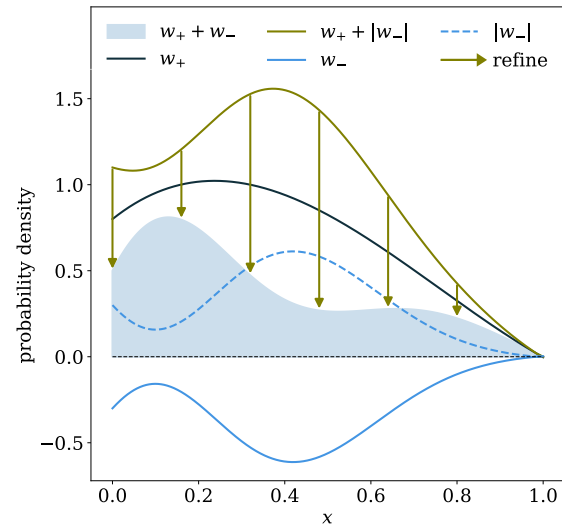
# Neural refinement of weights (Dennis Noll)

Use  $NV$  to distinguish pos. & neg. event

$\leadsto$  use this to reweight

## Weight Transformation: Refiner **NEW!**

- Learn residual weight spectrum
- Train classification between:
  - Samples with positive weights  $w_+$
  - Samples with negative weights  $|w_-|$
- Application:
  - One refinement factor  $r$  per phase space  $x$
  - $w_{\text{new}} = r \cdot |w_{\text{old}}|$



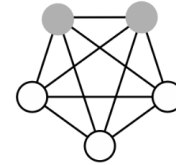
# QCD & information theory (Ben Asi)

measure log moments of eq. thrust

## QCD Theory meets Information Theory

**Boltzman machine:** Generative model samples according to stat dist

$$P(s) \sim e^{-E/T}, \quad E = - \sum_{i < j} w_{ij} s_i s_j - \sum_i \theta_i s_i$$



**Boltzman factor:** Maximum entropy solution subject to constraint on average energy

$$p(x) = \overset{\text{Prior}}{\downarrow} q(x) \exp \left[ \overset{\text{Sets Partition Function}}{\downarrow} -\beta_0 - \underset{\substack{\uparrow \\ \text{Lagrange Multiplier}}}{\beta_1} \underset{\substack{\uparrow \\ \text{Constrained Quantity}}}{f_1(x)} - \beta_2 f_2(x) - \dots \right]$$

HEP  $\rightarrow$    $\leftarrow$  ML

**Sudakov structure:** Plucking a random event-shape observable distribution

$$r(\tau)_{\text{LL,f.c.}} = \frac{-2\alpha_s C_F}{\pi} \frac{\ln \tau}{\tau} \exp \left[ -\frac{\alpha_s C_F}{\pi} \ln^2 \tau \right]$$

Sudakov factor

**ML practitioner:** Sudakov = Boltzmann factor and cusp AD = Lagrange multiplier  
that enforces constraint on the 2nd log moment of distribution

*log moments not previously measured or calculated before in QCD!*

# Resampling for event generators

(Simon Plätzer)

( sorry missed the talk )

## Conclusion

- This is a very important problem which needs fixing!
- Many ideas, some easier to implement some harder

BUT

do we need an event generator here?

→ simplified analysis