## **MadWeight**

#### automatic event reweighting with matrix elements

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# **Motivation and plan**

- motivation : method to maximize the information that you can extract from a sample of events : matrix element method
  - test theoretical hypothesis
  - need a good understanding of the detector
  - we can extract mass, spin, cross section,...
- 🍠 plan
  - weighting experimental events
  - MadWeight : automatic computation of the weights
  - Examples of application

matrix element method : weighting events

 $P(\boldsymbol{x}, \alpha) =$ 

$$|M_{lpha}|^2(oldsymbol{x})$$

where

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matrix element method : weighting events

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 $|M_{\alpha}|^2(\boldsymbol{y})W(\boldsymbol{x},\boldsymbol{y})|$ 

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- $W(\boldsymbol{x}, \boldsymbol{y})$  is the resolution function
  - x : experimental measurements
  - y : partonic momenta

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  - $\checkmark$   $d\phi(y)$  is the partonic phase-space measure

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• matrix element method : weighting events  $P(\boldsymbol{x}, \alpha) = \frac{1}{\sigma} \int d\phi(\boldsymbol{y}) dw_1 dw_2 f_1(w_1) f_2(w_2) |\boldsymbol{M}_{\alpha}|^2(\boldsymbol{y}) W(\boldsymbol{x}, \boldsymbol{y})$ 

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  - x : experimental measurements
  - y : partonic momenta
  - $\checkmark$   $d\phi(y)$  is the partonic phase-space measure
  - $f_1(w_1), f_2(w_2)$  are the Parton Distribution Functions

#### How to evaluate the weight?

matrix element method : weighting events

 $P(\boldsymbol{x},\alpha) = \frac{1}{\sigma} \int d\phi(\boldsymbol{y}) dw_1 dw_2 f_1(w_1) f_2(w_2) |\boldsymbol{M}_{\alpha}|^2(\boldsymbol{y}) W(\boldsymbol{x},\boldsymbol{y})$ 

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- transfer functions : experimental extraction
- numerical integration : very difficult due to the structure in peaks of the integrand

 $|M_{lpha}(oldsymbol{y})|^2$  : propagators

$$W(\boldsymbol{x}, \boldsymbol{y}) \approx \prod_{i} \frac{1}{\sqrt{2\pi\sigma_i}} e^{-\frac{(x_i - y_i)^2}{2\sigma_i^2}}$$

### **Decay chain example**

let us consider a specific example of decay chain :



peaks in |M<sub>\alpha</sub>(y)|<sup>2</sup> controlled by m<sup>\*</sup><sub>-1</sub>,..., m<sup>\*</sup><sub>-7</sub> (7 variables)
peaks in W(x, y) controlled by
\(\theta\_i, \phi\_i | ^2 \) i \(\in \{2, 3, 4, 5, 6, 7, 8\}\) (21 variables)

## **Decay chain example**

MadWeight decomposes it into blocks corresponding to local change of variables



Block D Block D Block D

final parametrization :

$$d\phi = d|\mathbf{p}_2|d|\mathbf{p}_3|d|\mathbf{p}_4|d|\mathbf{p}_6|\prod_{i=2}^8 d\theta_i d\phi_i \prod_{j=1}^7 dm_{-j}^{*2} \times J$$

## MadWeight code

in general in MadWeight algorithm,

- the phase-space is splitted into *blocks*, each of them is associated to a specific local change of variables
- we only consider analytic changes of variables
- 12 different changes of variables are available
- the decomposition into blocks depends on the topology, on the widths of the Breit-Wigner distributions, and on the shape of the resolution function  $\rightarrow$  MadWeight

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$$L(m_t) = e^{-N \int P(\boldsymbol{x}, m_t) d\boldsymbol{x}} \prod_{i=1}^N P(\boldsymbol{x}_i; m_t)$$

Input :  $m_{top} = 160 \text{ GeV}$ , output :  $m_{top} = 158.9 \pm 2.3 \text{ GeV}$ 



Higgs mass analysis



Higgs mass analysis



- 500 Monte Carlo events (MadGraph/Pythia/PGS)
- input :  $m_{Higgs} = 300$  GeV, output :  $m_{Higgs} = 300.9 \pm 3.0$  GeV







 $M_{H^+} = 100 {\rm GeV}$ 



• 
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0.2

0.4

0.6

0.8



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$$M_{H^+} = 100 {\rm GeV}$$



- 750 background events
- 262 signal events

$$r = 25.9\%$$



$$M_{H^+} = 100 {\rm GeV}$$



#### Conclusion

- the Matrix Element method provides the best discriminator on an event-by-event basis
- both theoritical ( $|M|^2$ ) and experimental ( $\boldsymbol{x}, W(\boldsymbol{x}, \boldsymbol{y})$ ) information is used
- the computation of the weights requires a specific phase space generator : MadWeight
  - finds the best phase-space parametrisation(s)
  - fully automatic
  - works for "any" decay chain
- code available on madgraph.phys.ucl.ac.be (on the download page)

#### End

combine the weights into a likelihood

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- 72 events
- $M_{top} = 180.1 \pm 3.6_{stat} \pm$  $4.0_{sys}\,\mathrm{GeV}$
- J. Estrada : Phd dissertation, University of Rochester (2001)

- efficiency of an adaptative MC integration :
  - case 1 : any peak is aligned along a single direction of the P-S parametrization



 $\rightarrow$  the adaptative Monte-Carlo P-S integration is very efficient

- efficiency of an adaptative MC integration :
  - case 2 : some peaks are not aligned along a single direction of the P-S parametrization

![](_page_33_Figure_3.jpeg)

 $\rightarrow$  the adaptative Monte-Carlo P-S integration converges slowly

efficiency of an adaptative MC integration :

possible solution : perform a change of variables

![](_page_34_Figure_3.jpeg)

 $\rightarrow$  the adaptative Monte-Carlo P-S integration is very efficient

efficiency of an adaptative MC integration :

case 3 : there are more peaks than phase-space variables

![](_page_35_Figure_3.jpeg)

 $\rightarrow$  the efficiency depends of the shape, relative position, ... of the peaks

# **Phase-space generation**

![](_page_36_Figure_1.jpeg)

- peaks in  $|M_{lpha}(oldsymbol{y})|^2$  controlled by  $m^*_{-1},\ldots,m^*_{-4}$  (4 variables)
- peaks in  $W(\boldsymbol{x}, \boldsymbol{y})$  controlled by  $\theta_i, \phi_i, |p_i|^2 \quad i \in \{1, 2, 3, 4\}$  (12 variables)
- $dim[d\phi] = 16$ ,  $\rightarrow$  each peak can be aligned along a single variable of integration

#### **Phase-space generation**

which parametrization do we use?

natural parametrization

$$d\phi = \prod_{i=1}^{4} \frac{d^3 p_i}{(2\pi)^3 2E_i} \prod_{i=5}^{6} \frac{d^3 p_i}{(2\pi)^3 2E_i} dx_1 dx_2 \delta^4 \left( p_a + p_b - \sum_j p_j \right)$$

where all the peaks in  $W(\boldsymbol{x}, \boldsymbol{y})$  are aligned

we apply local changes of variables to reach the parametrization

$$d\phi = \prod_{i=1}^{4} \frac{d\theta_i d\phi_i d|\mathbf{p}_i|}{\prod_{j=1}^{4} \frac{dm_{-j}^{*2} \times J}{\sum_{i=1}^{4} \frac{dm_{-j}^{*2}}{\sum_{i=1}^{4} \frac{dm_{-j}}{\sum_{i=1}^{4} \frac{dm_{-j}}{\sum_{i=1}^{4}$$

where each Breit-Wigner distribution is also aligned

## **MadWeight : changes of variables**

changes of variables to restore energy momentum conservation

![](_page_38_Picture_2.jpeg)

![](_page_38_Figure_3.jpeg)

Class A

![](_page_38_Figure_5.jpeg)

#### **MadWeight : changes of variables**

auxiliary changes of variables :

![](_page_39_Figure_2.jpeg)

- advantages :
  - it takes into account the full matrix element (in particular spin-correlation effects)
  - resolution of the detector is included
  - it is particularly usefull for processes with missing particles
- drawbacks :
  - the evaluation of the weight is time-consuming compare to other methods
  - what are the systematics errors?