

# MoMEMta, a software for the computation of the Matrix Element weights

Florian Bury

Supervisor : Christophe Delaere

*When the M meets the P*



December 13, 2018

# Matrix Element Method (MEM)

## Objective

$P(x|\alpha)$  = Probability to observe an experimental event  $x$ , given a specific theoretical hypothesis  $\alpha$

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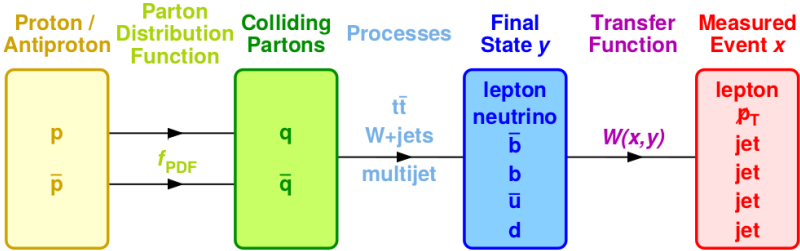
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Where  $d\phi(y) = \left( \prod_{i=3}^N \frac{d^3 P_i}{2E_i (2\pi)^3} \right) (2\pi)^4 \delta^4(P_1 + P_2 - \sum_{j=3}^N P_j)$



arXiv:1003.1316

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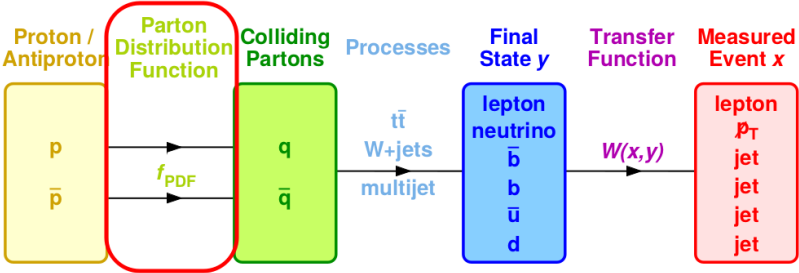
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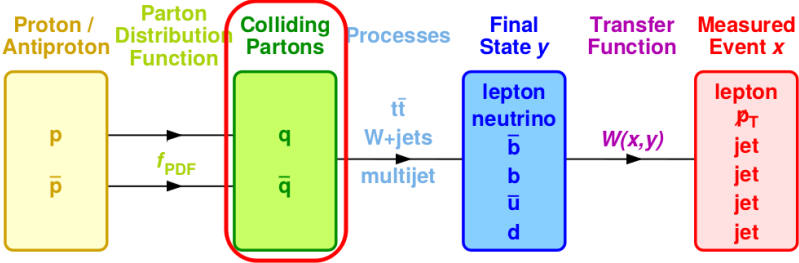
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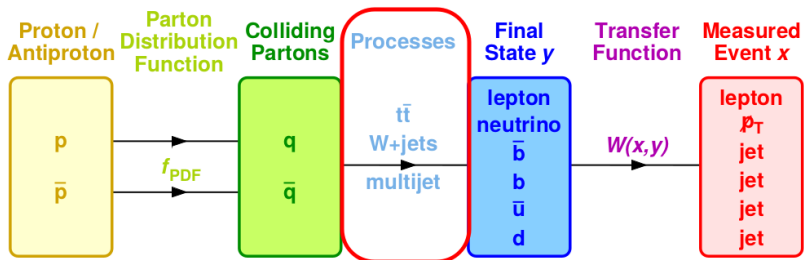
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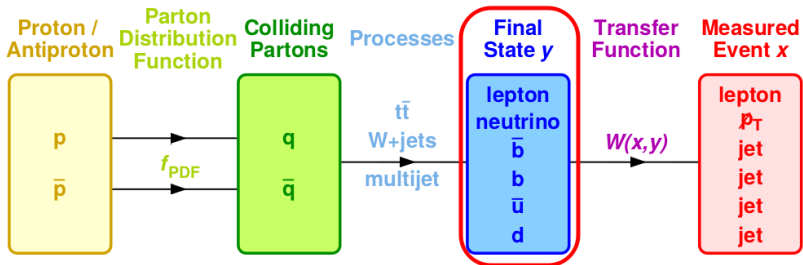
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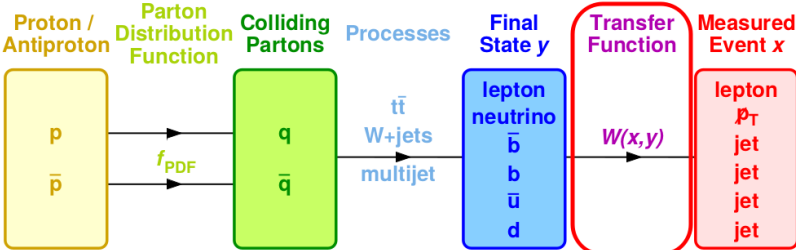
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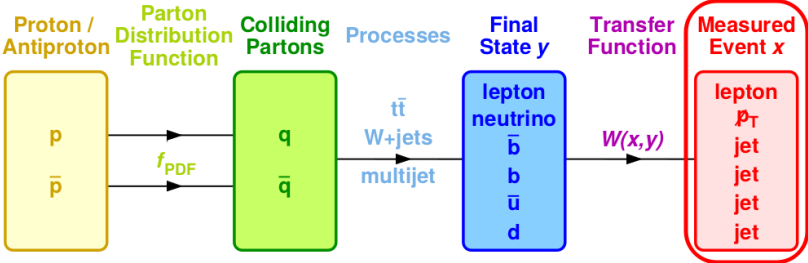
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## Applications

- Likelihood :  $-\ln(L) = -\sum_{i=1}^N \ln(P(x_i|\alpha))$
- Discriminant between two hypotheses  $\alpha$  and  $\beta$  (eg sig and bkgd) :  
$$\mathcal{D}(x) = \left( 1 + \frac{P(x|\alpha)}{P(x|\beta)} \right)^{-1}$$

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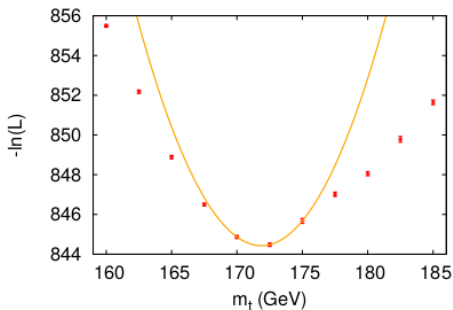
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$P(x|\alpha) = \text{Prob}$

## Computation

$$P(x|\alpha) = \frac{1}{\sigma_\alpha^{\text{vis}}}$$

When



, given a specific

$|q_2, y|^2 W(x|y)$

$\sum_{j=3}^N P_j$

1

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<sup>1</sup> arXiv:1007.3300

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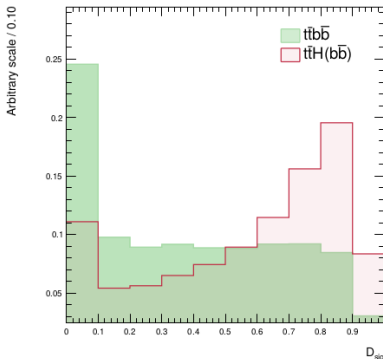
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$P(x|\alpha) = \text{Probability of observing event } x, \text{ given a specific } \alpha$

## Computation

$$P(x|\alpha) = \frac{1}{\sigma_\alpha^{\text{vis}}} \int_y d\phi$$

Where  $d\phi$  is the phase space element



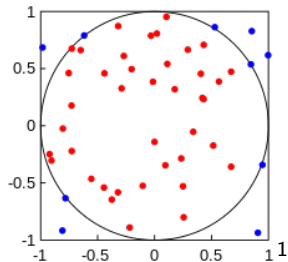
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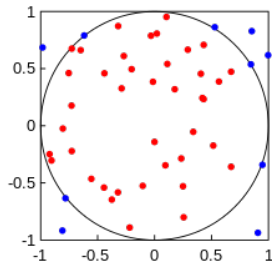
# Monte Carlo Integration



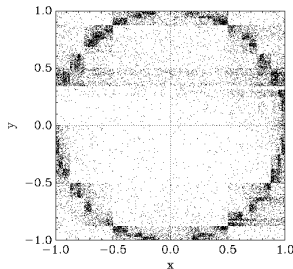
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<sup>1</sup>[wikipedia.org/wiki/Monte\\_Carlo\\_integration](https://en.wikipedia.org/wiki/Monte_Carlo_integration)

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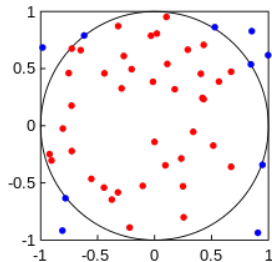
⇒  
Stratified  
sampling



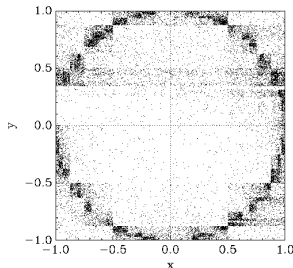
2

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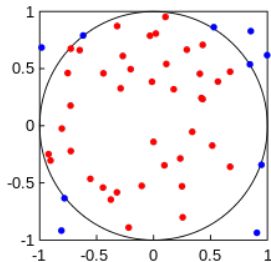
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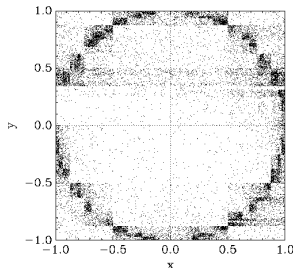
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Alternative : **Importance sampling**

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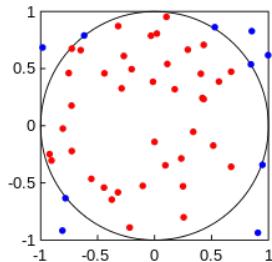
Alternative : **Importance sampling**

- 1  $S_\alpha = \frac{1}{N} \sum_{i=1}^N \frac{f(\vec{x}_i)}{p(\vec{x}_i)}$  and  $\sigma_\alpha^2 = \frac{1}{N-1} \left( \frac{1}{N} \sum_{i=1}^N \frac{f^2(\vec{x}_i)}{p(\vec{x}_i)} - S_\alpha^2 \right)$
- 2  $p(\vec{x}) \rightarrow p'(\vec{x})$  to reduce  $\sigma_\alpha^2$
- 3  $\alpha = \alpha + 1$  and back to step **1** unless  $\sigma_\alpha^2$  stops decreasing

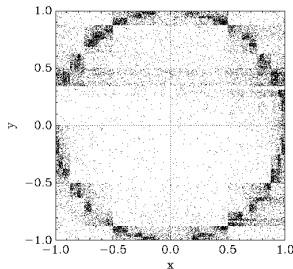
Final result :  $Integral = \bar{S} = \bar{\sigma}^2 \sum_\alpha \frac{S_\alpha}{\sigma_\alpha^2}$  and  $\frac{1}{\bar{\sigma}^2} = \sum_\alpha \frac{1}{\sigma_\alpha^2}$



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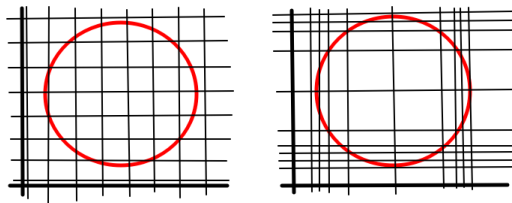


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# MoMEMta

A Modular toolkit for the Matrix Element Method at the LHC

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$$W(x|y) = \prod_{i=1}^n W(x^i|y^i) \text{ for each particle } i$$

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- $W(x|y)$  : resolutions of the different detected variables

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Objective : strength of each peak mapped onto a single variable of integration

$$\text{For } W(x|y) : d\phi(y) = \left( \prod_{i=3}^N \frac{d^3 P_i}{2E_i (2\pi)^3} \right) (2\pi)^4 \delta^4(P_1 + P_2 - \sum_{j=3}^N P_j)$$

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$\Downarrow$

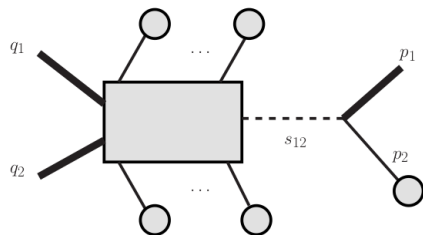
**MoMEMta**

- Main Blocks : change of variables and integration of the  $\delta^4$
- Secondary Blocks : change of variables



# MoMEMta Blocks examples

## Main Block B :



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Removes  $q_1, q_2$  and  $\vec{P}_1$

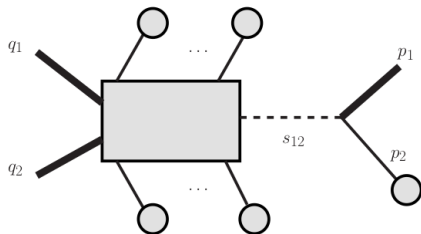
Integrate over  $s_{12}$

Part of the integrand concerned by this change :

$$dq_1 dq_2 \frac{d^3 P_1}{(2\pi)^3 2E_1} (2\pi)^4 \delta^4(P_{in} - P_{fin})$$

$$\downarrow$$
$$\frac{1}{4\pi E_1} ds_{12} \times J$$

$$J = \frac{E_1}{s} |p_{2z} E_1 - E_2 p_{1z}|^{-1}$$



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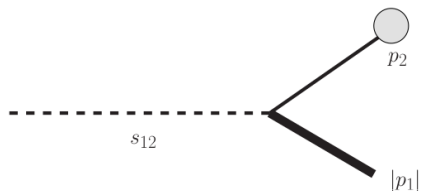
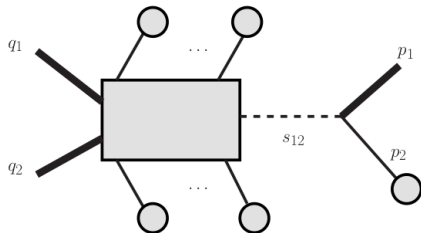
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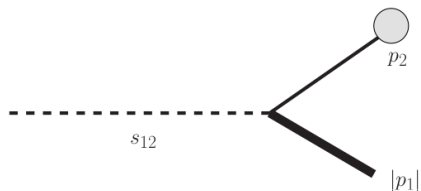
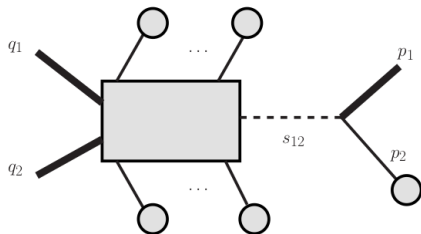
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$$\frac{d^3 P_1}{(2\pi)^3 2E_1}$$

$\downarrow$

$$\frac{1}{(2\pi)^3 2E_1} d\phi_1 d\theta_1 ds_{12} \times J$$

$$J = \frac{E_1}{2} \sin\theta_1 |\vec{P}_1|^2 | |\vec{P}_1| E_2 - E_1 \hat{P}_1 \cdot \vec{P}_2 |^{-1}$$



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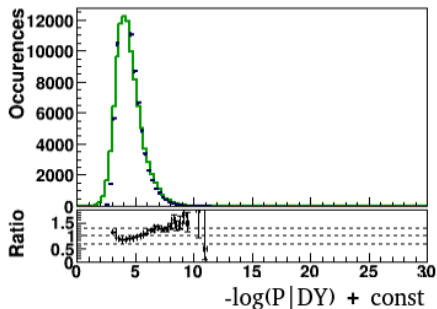
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$$D(x) = \frac{P(x|t\bar{t} \rightarrow llbb)}{P(x|t\bar{t} \rightarrow llbb) + P(x|DY \rightarrow llbb)}$$

**DY sample**

