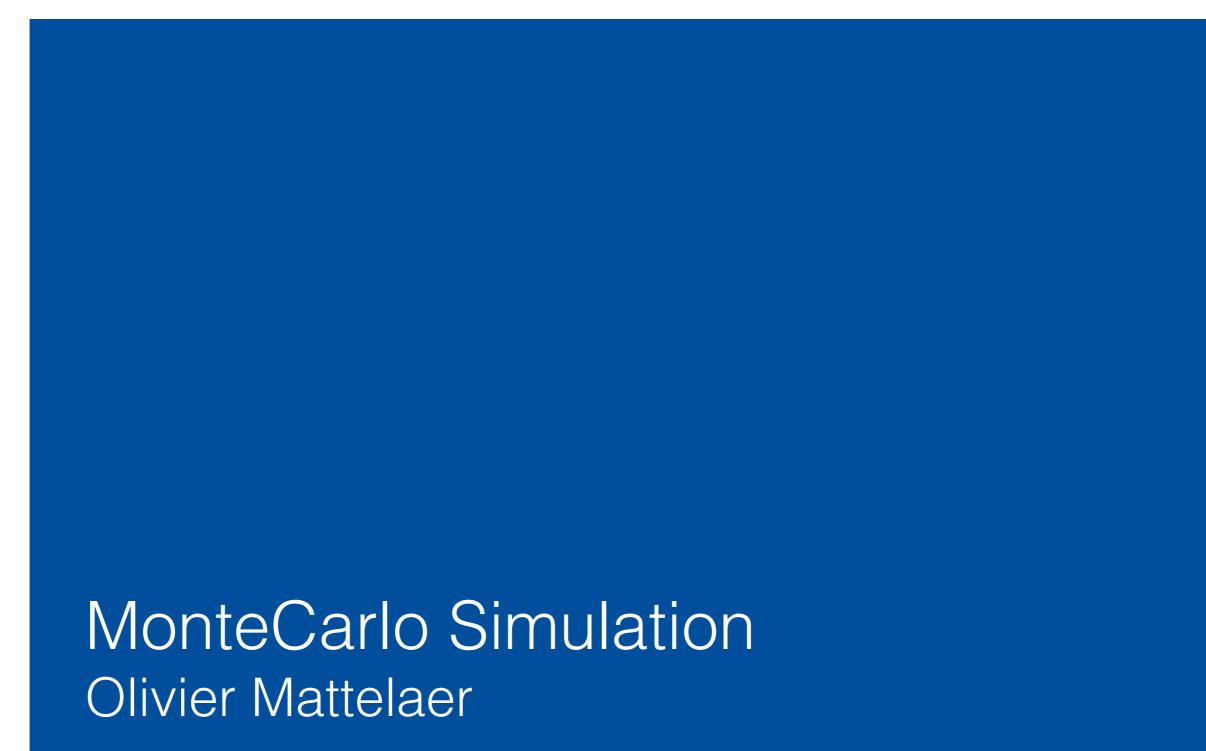
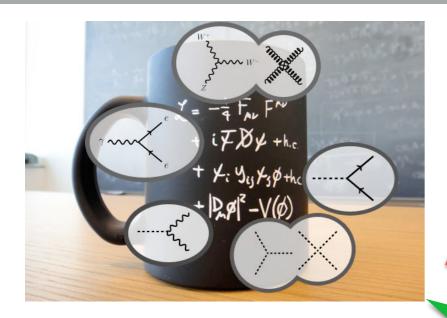
UCLouvain

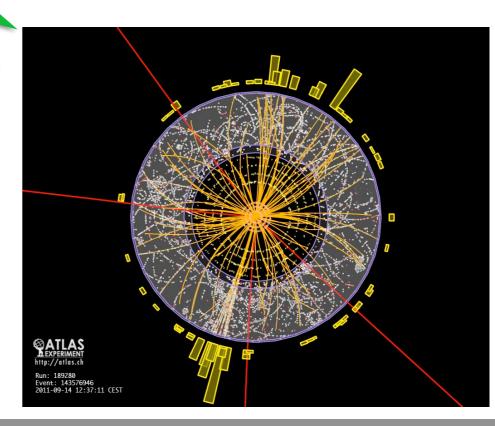
Institut de recherche en mathématique et physique Centre de Cosmologie, Physique des Particules et Phénoménologie

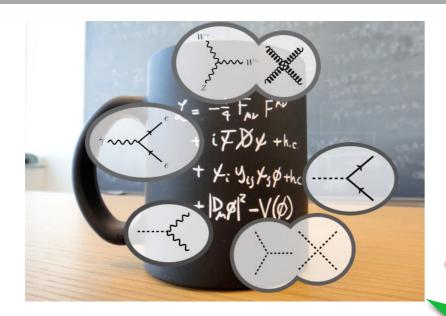






Monte-Carlo Physics

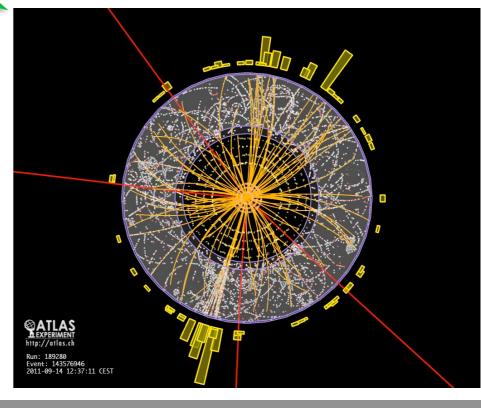




Monte-Carlo Physics

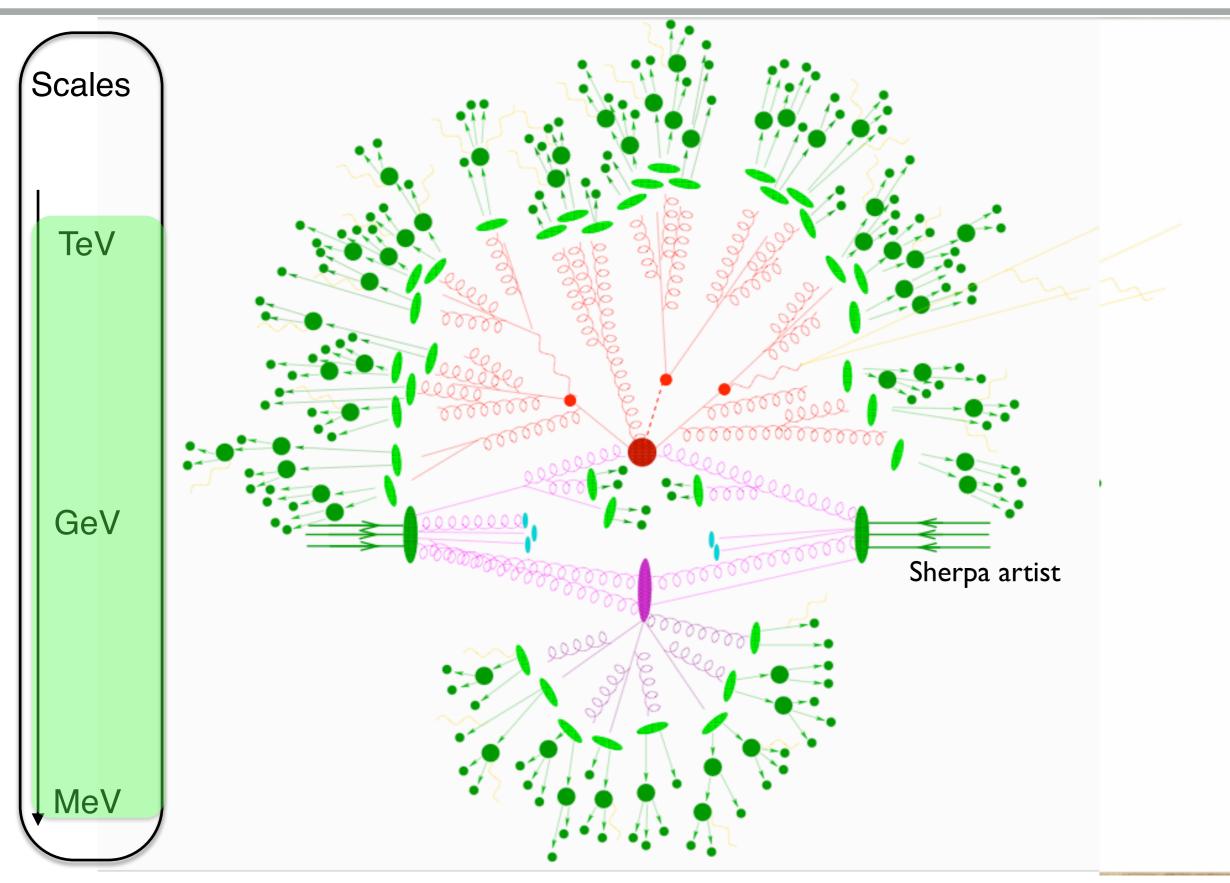
Our goal

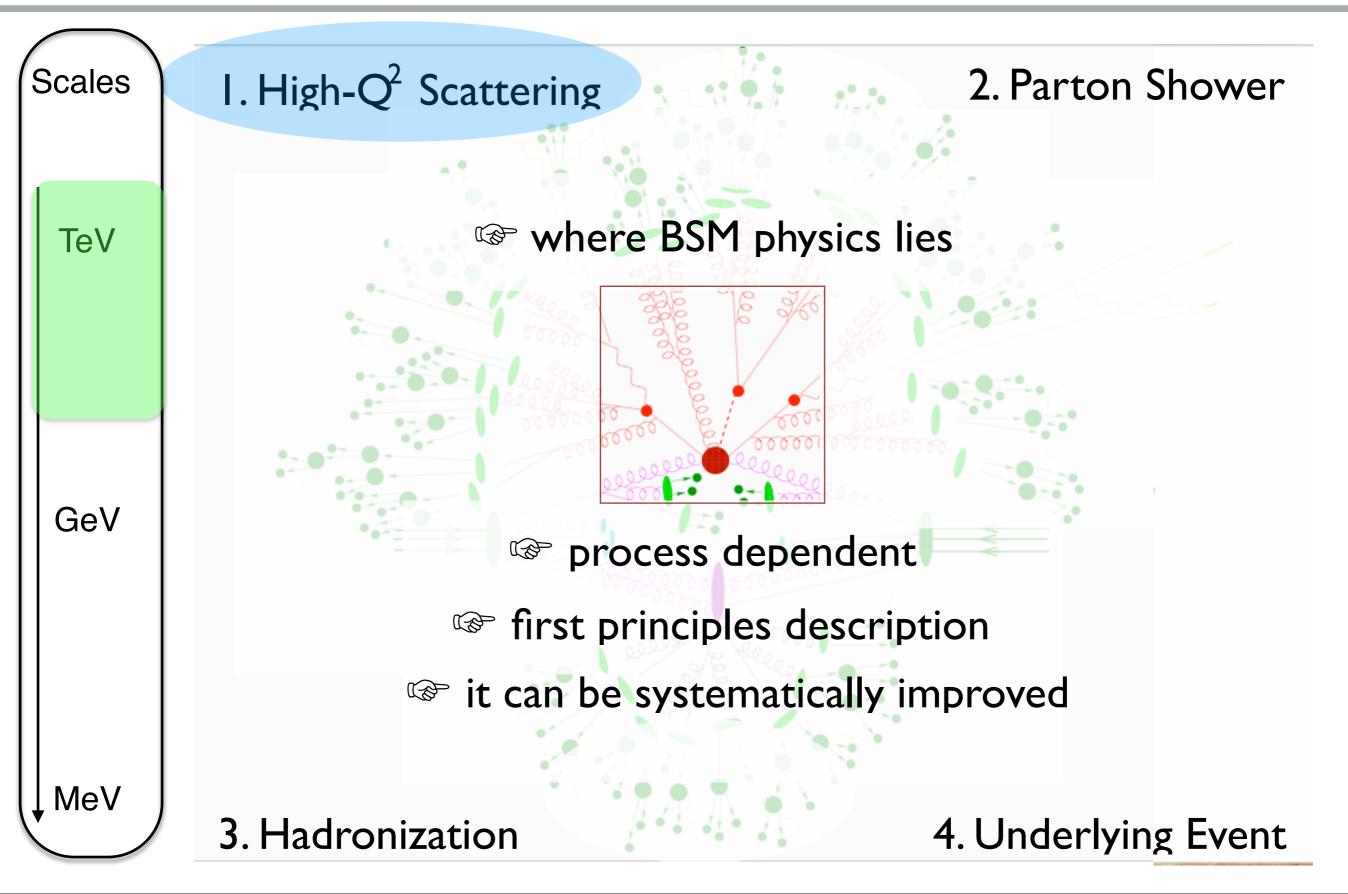
- Cross-section
- Differential cross-section
- Un-weighted events

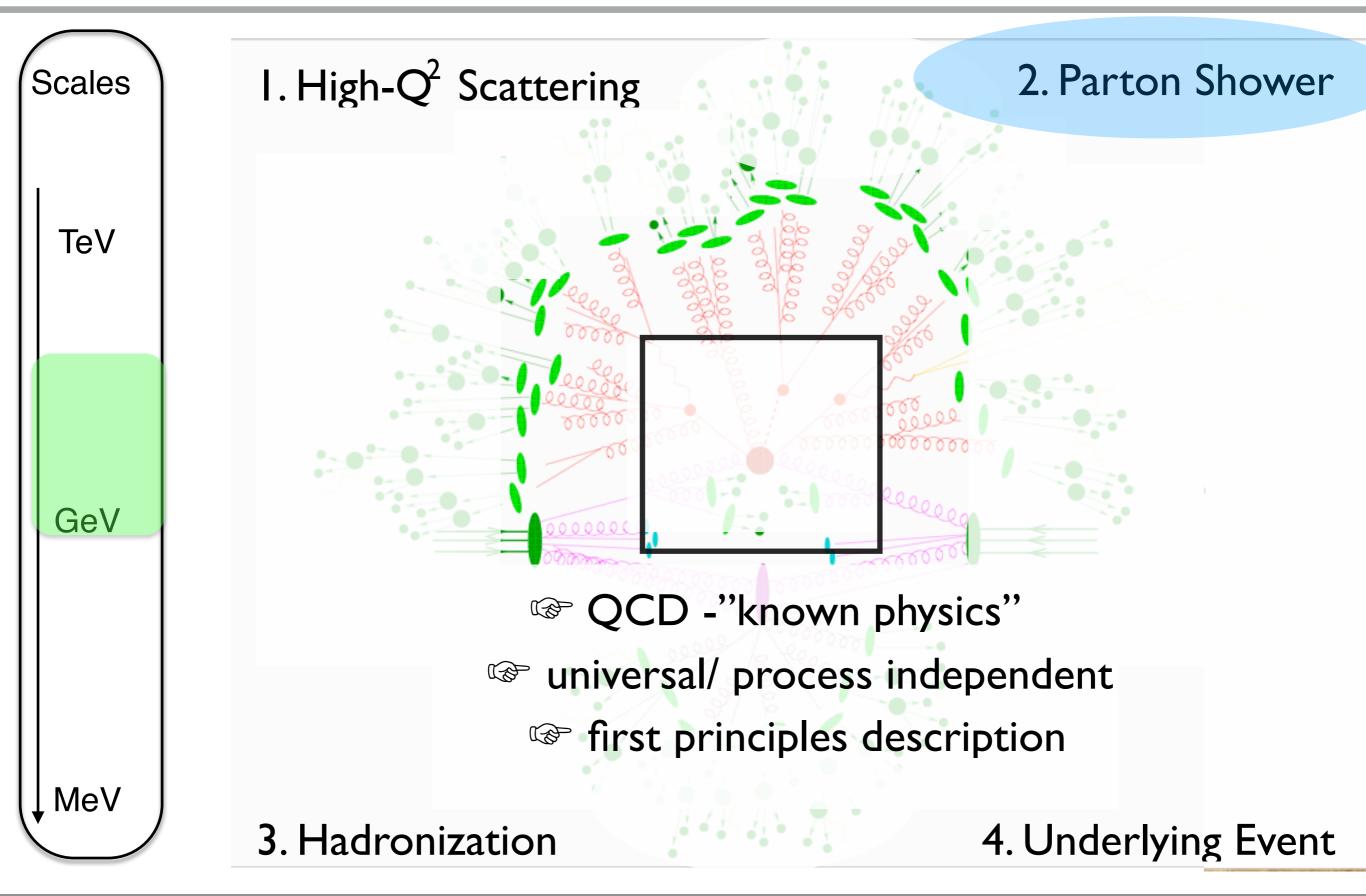


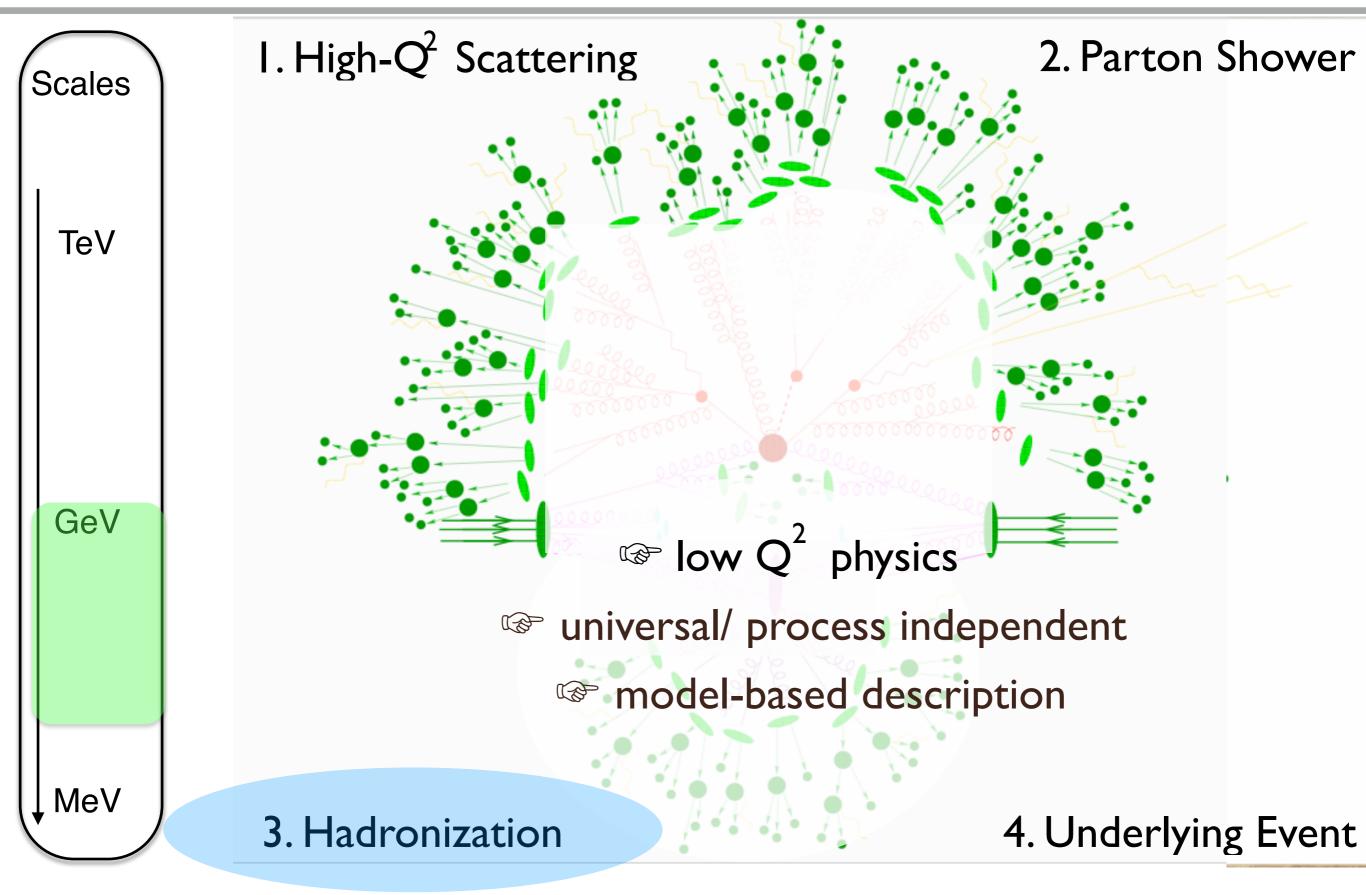
Simulation of collider events

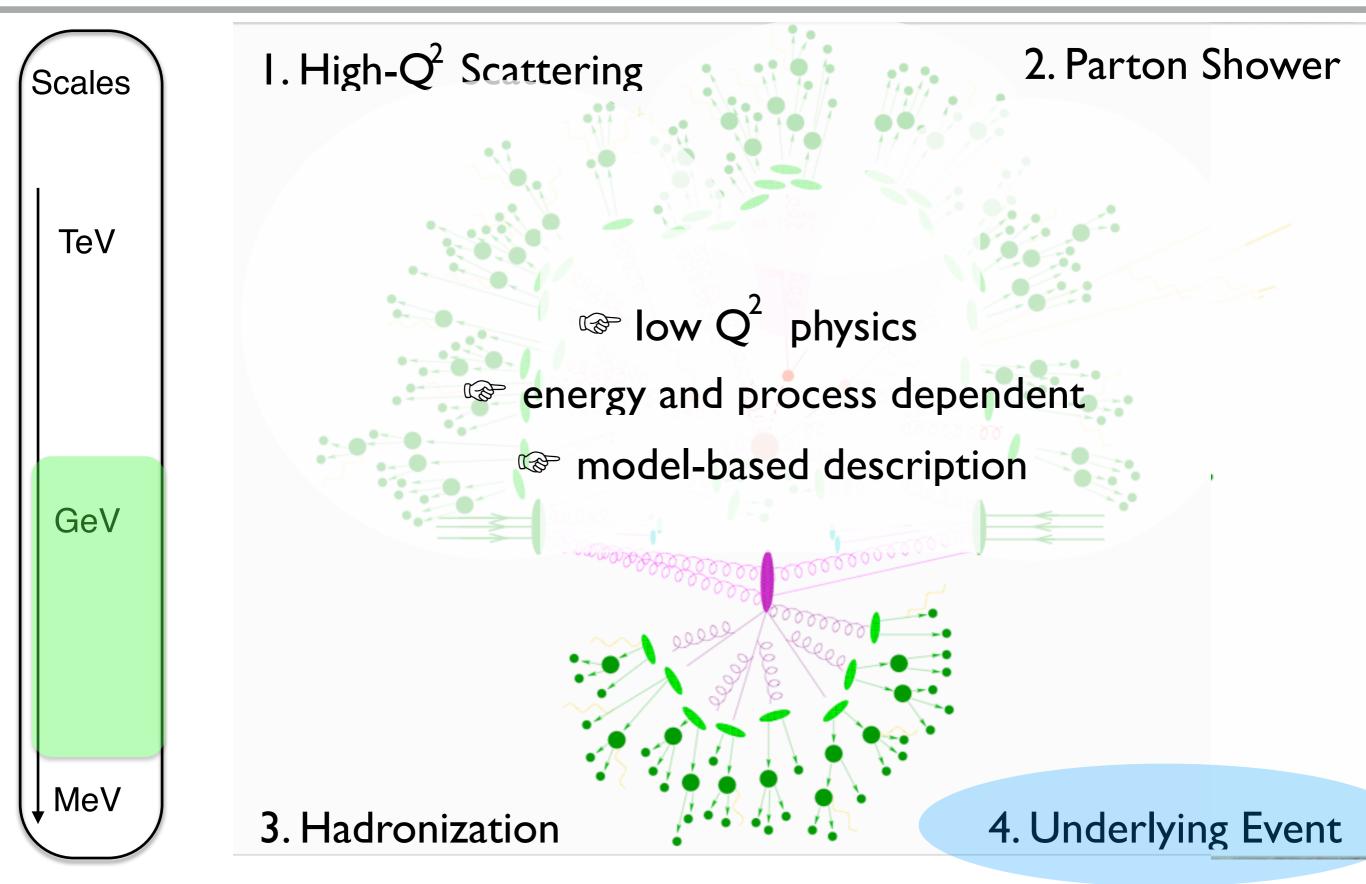
Simulation of collider events

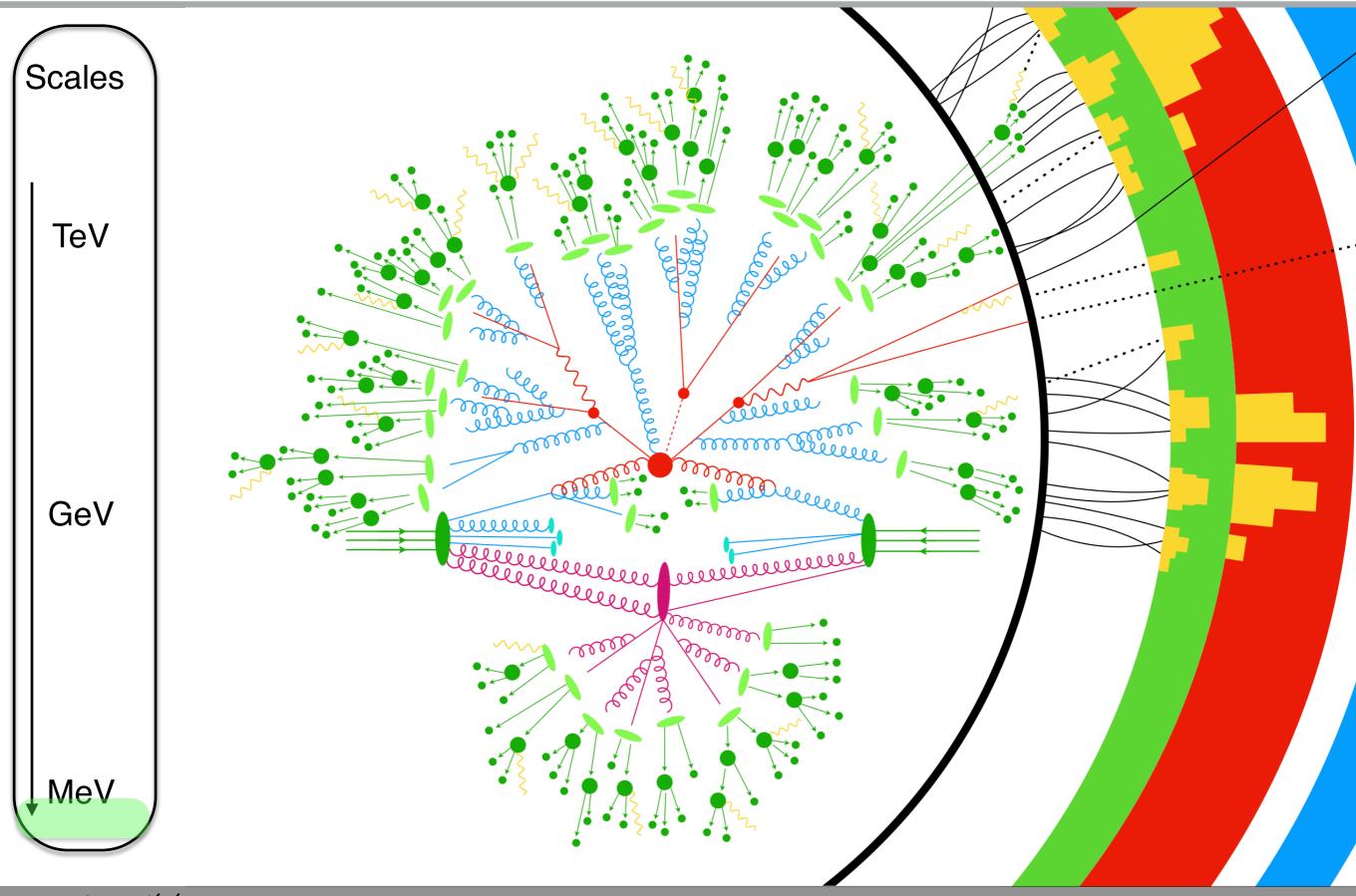












Question time



Allez sur wooclap.com

Entrez le code d'événement dans le bandeau supérieur

Code d'événement MADGRAPH

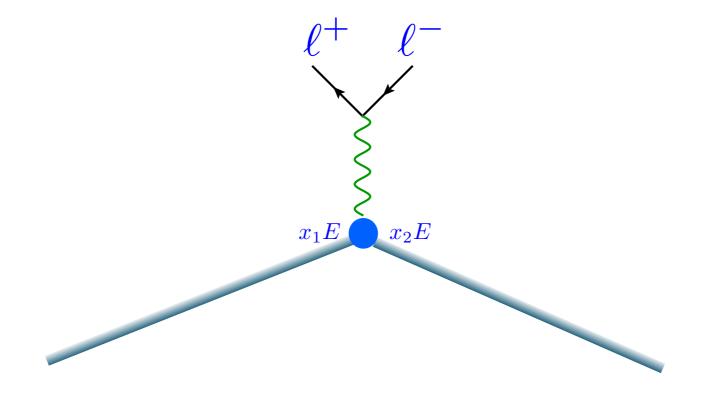
Activer les réponses par SMS

To Remember



- New physics visible only at High scale
- Problem split in different scale
 - Factorisation theorem

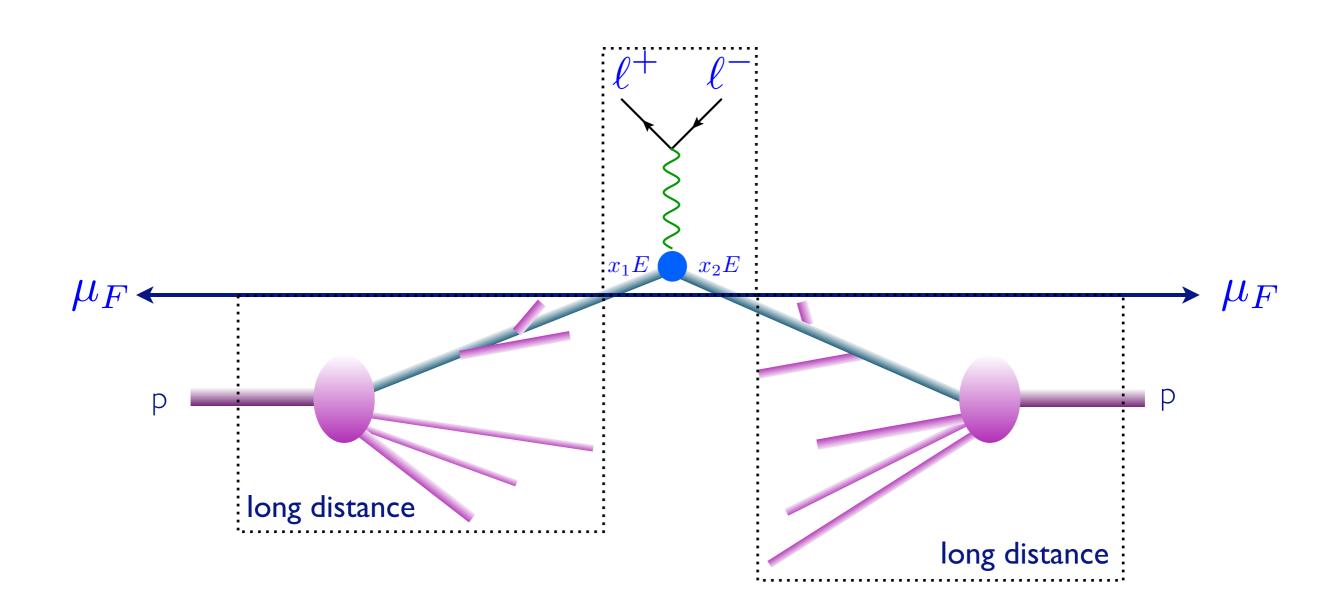
MASTER FORMULA FOR THE LHC



 $\hat{\sigma}_{ab\to X}(\hat{s},\mu_F,\mu_R)$

Parton-level cross section

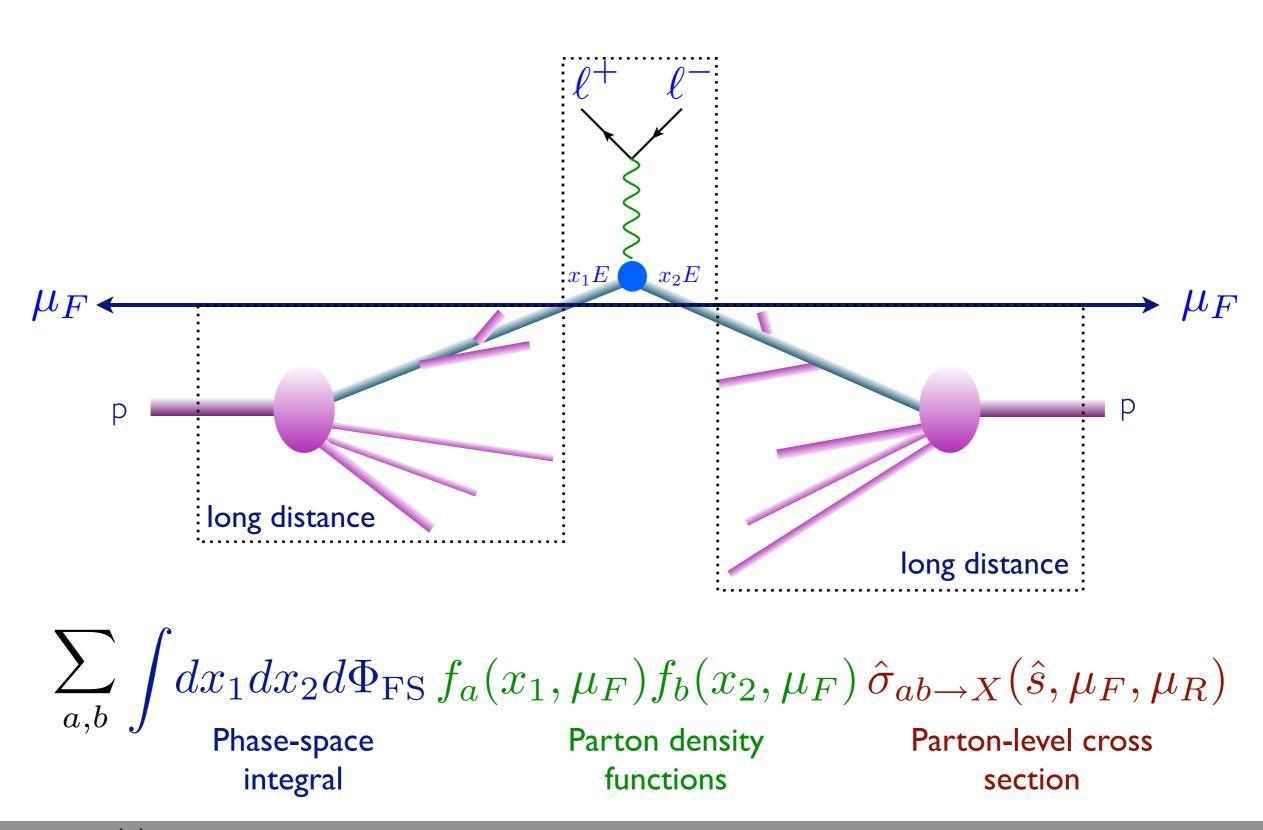
MASTER FORMULA FOR THE LHC



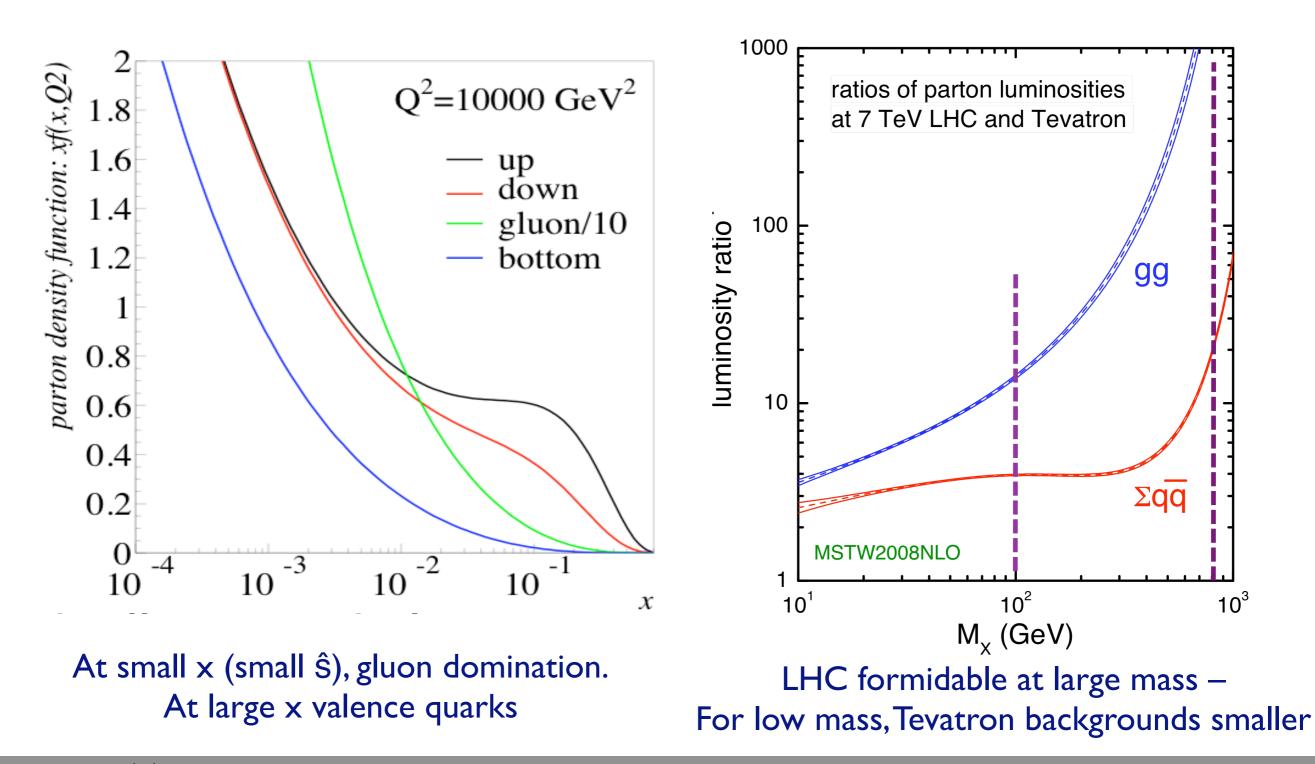
 $f_a(x_1, \mu_F) f_b(x_2, \mu_F) \hat{\sigma}_{ab \to X}(\hat{s}, \mu_F, \mu_R)$

Parton density functions Parton-level cross section

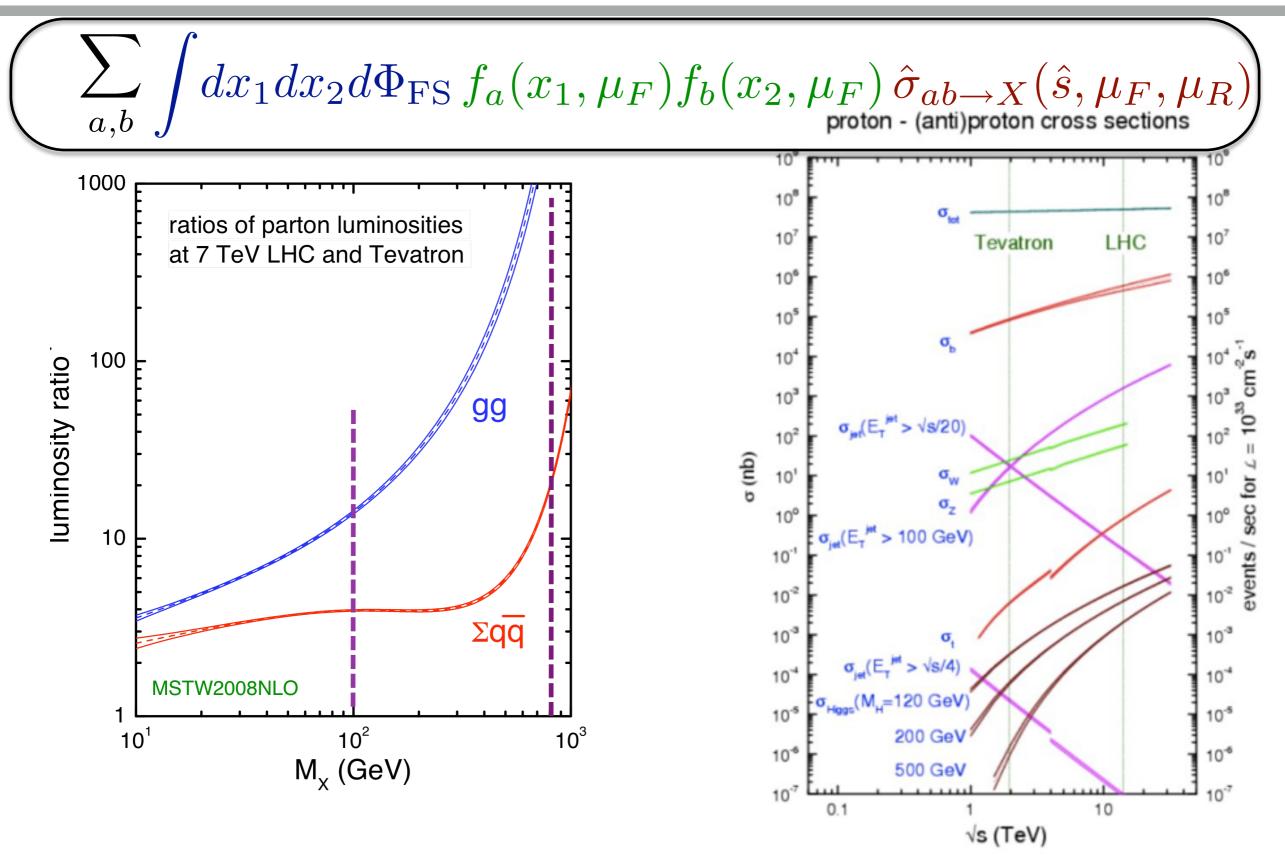
MASTER FORMULA FOR THE LHC

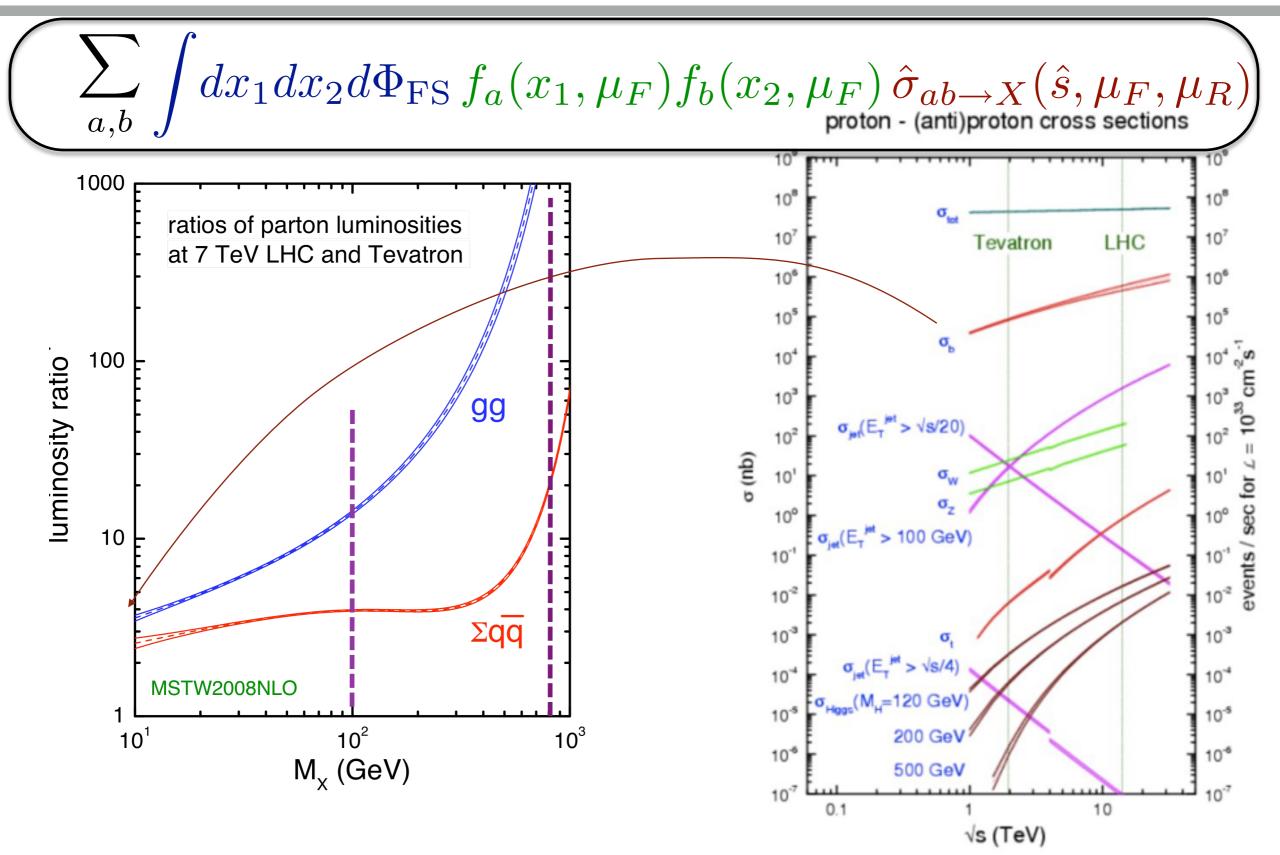


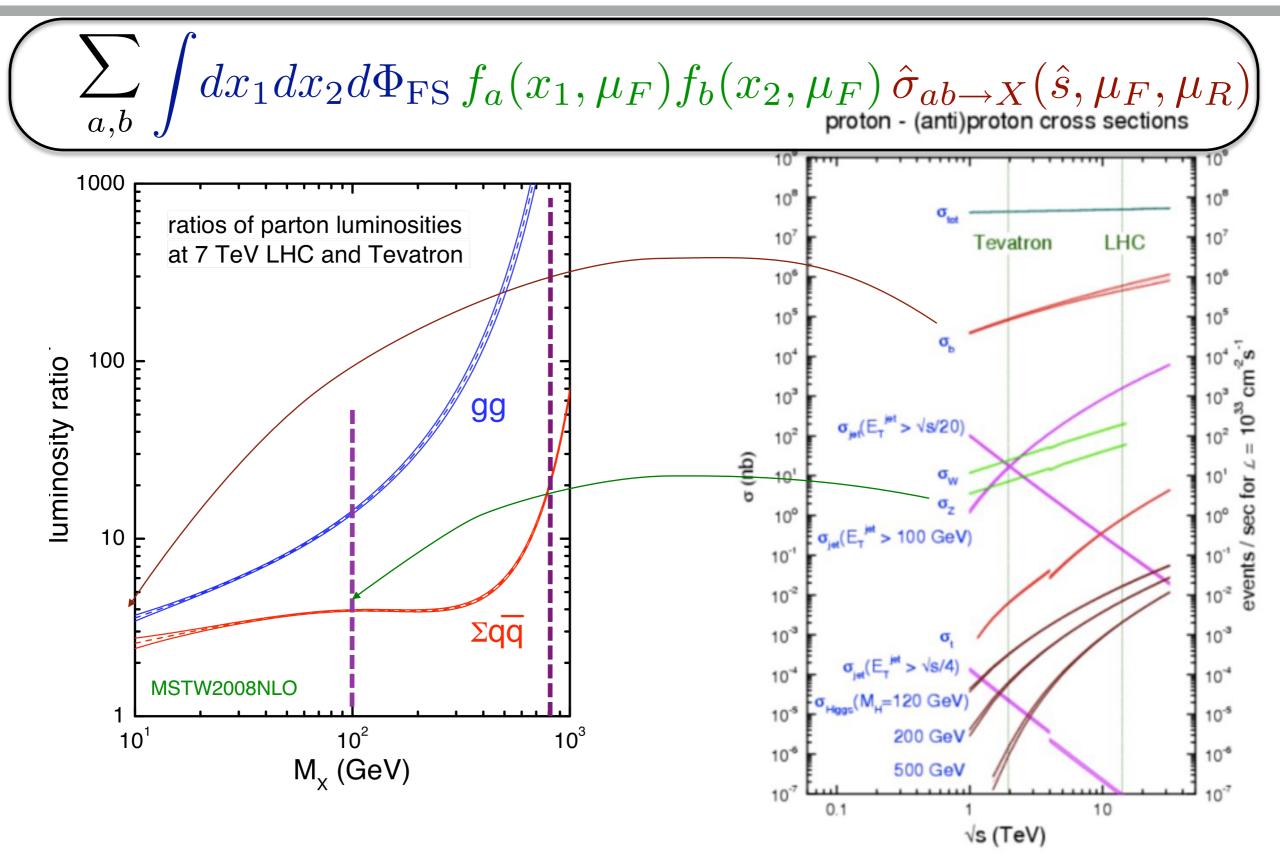
Parton densities

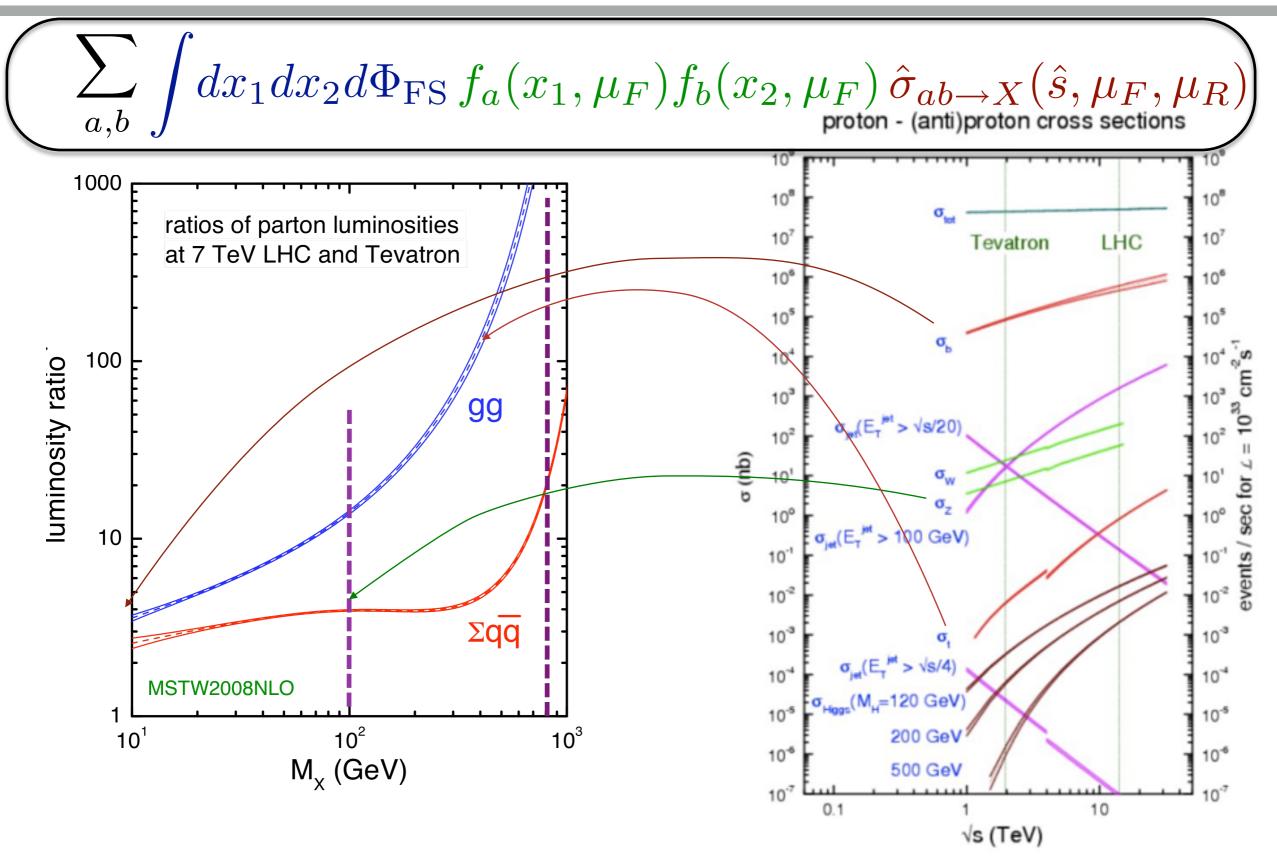


Mattelaer Olívíer









Perturbative expansion

$d\hat{\sigma}_{ab\to X}(\hat{s},\mu_F,\mu_R)$ Parton-level cross section

• The parton-level cross section can be computed as a series in perturbation theory, using the coupling constant as an expansion parameter, schematically:

$$\hat{\sigma} = \sigma^{\text{Born}} \left(1 + \frac{\alpha_s}{2\pi} \sigma^{(1)} + \left(\frac{\alpha_s}{2\pi}\right)^2 \sigma^{(2)} + \left(\frac{\alpha_s}{2\pi}\right)^3 \sigma^{(3)} + \dots \right)$$

Perturbative expansion

$d\hat{\sigma}_{ab\to X}(\hat{s},\mu_F,\mu_R)$ Parton-level cross section

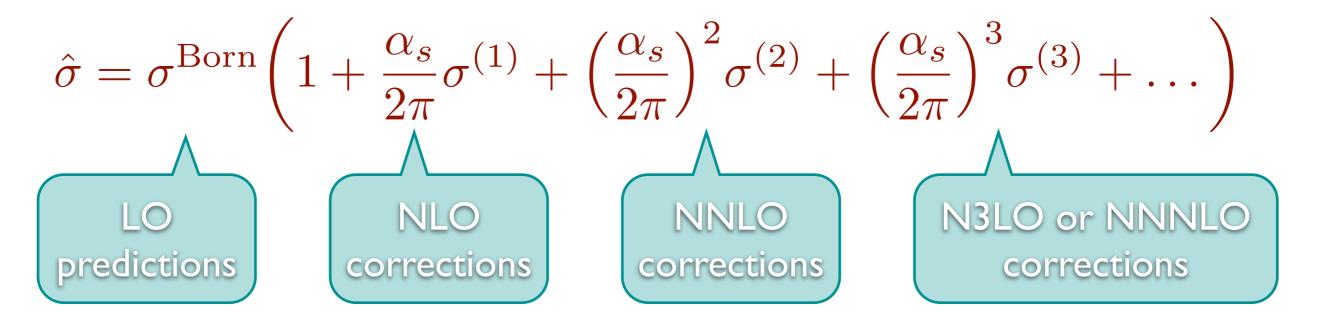
• The parton-level cross section can be computed as a series in perturbation theory, using the coupling constant as an expansion parameter, schematically:

$$\hat{\sigma} = \sigma^{\text{Born}} \left(1 + \frac{\alpha_s}{2\pi} \sigma^{(1)} + \left(\frac{\alpha_s}{2\pi}\right)^2 \sigma^{(2)} + \left(\frac{\alpha_s}{2\pi}\right)^3 \sigma^{(3)} + \dots \right)$$
LO
predictions

Perturbative expansion

$d\hat{\sigma}_{ab\to X}(\hat{s},\mu_F,\mu_R)$ Parton-level cross section

 The parton-level cross section can be computed as a series in perturbation theory, using the coupling constant as an expansion parameter, schematically:



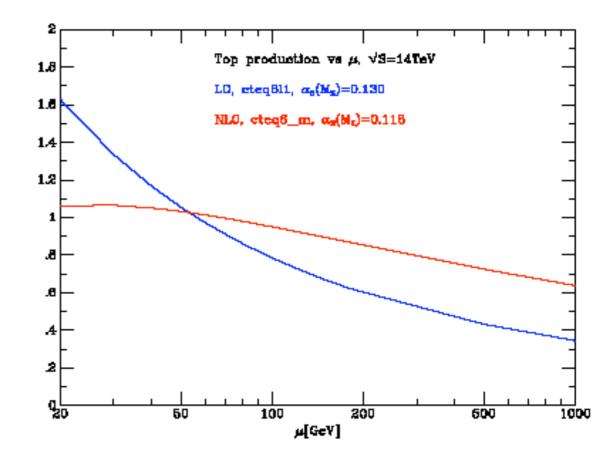
 Including higher corrections improves predictions and reduces theoretical uncertainties

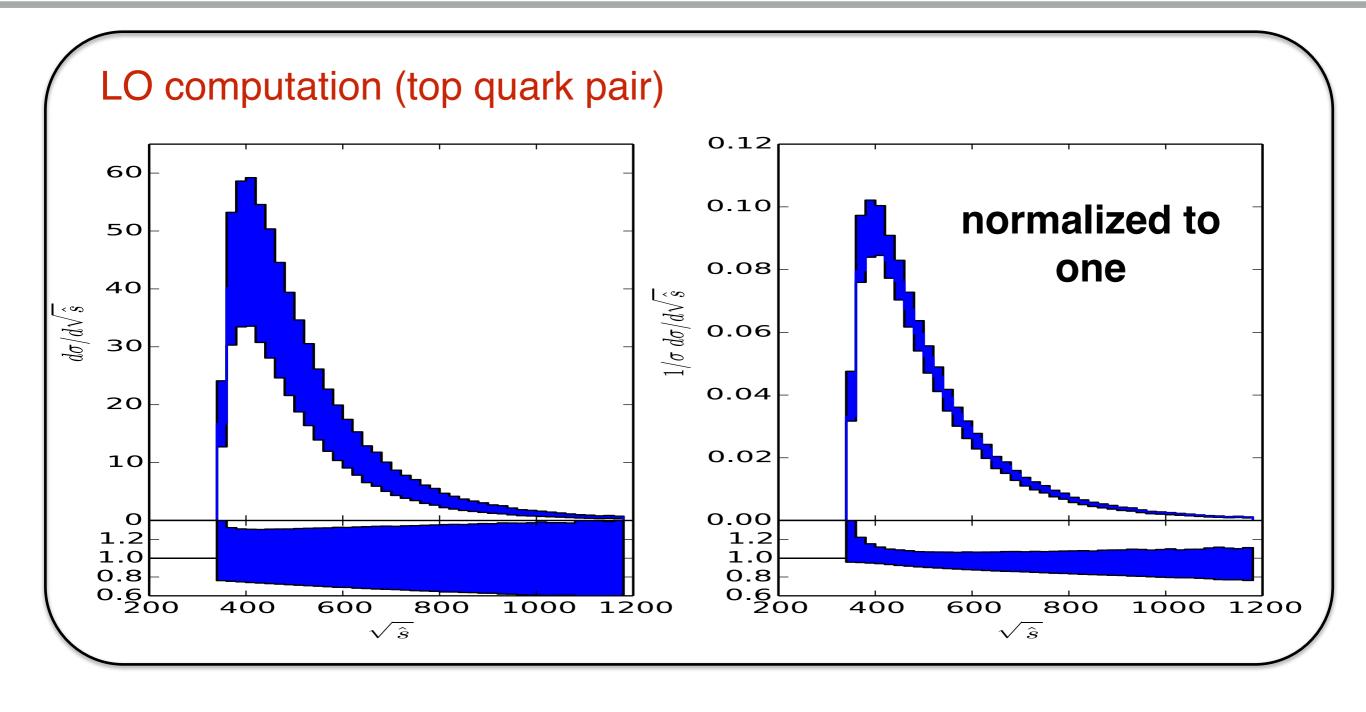
Improved predictions

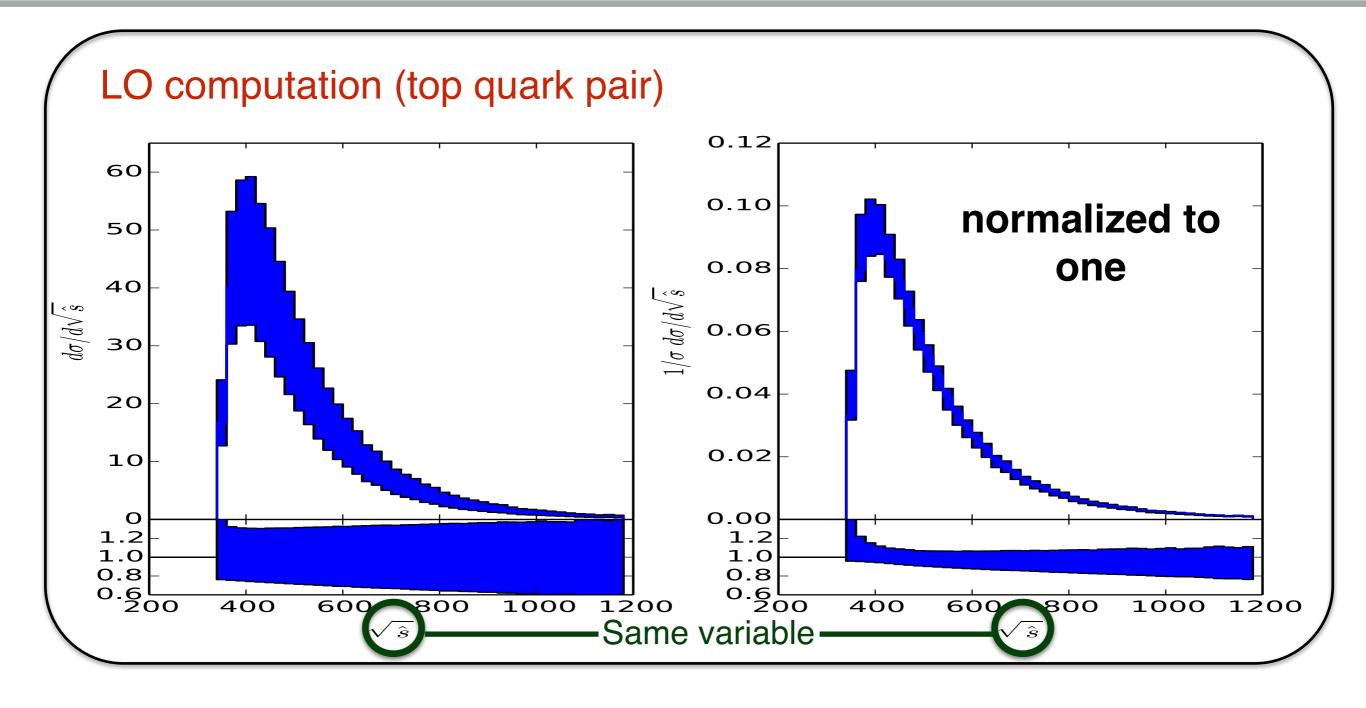
$d\sigma = \sum_{a,b} \int dx_1 dx_2 \ f_a(x_1, \mu_F) f_b(x_2, \mu_F) \, d\hat{\sigma}_{ab \to X}(\hat{s}, \mu_F, \mu_R)$

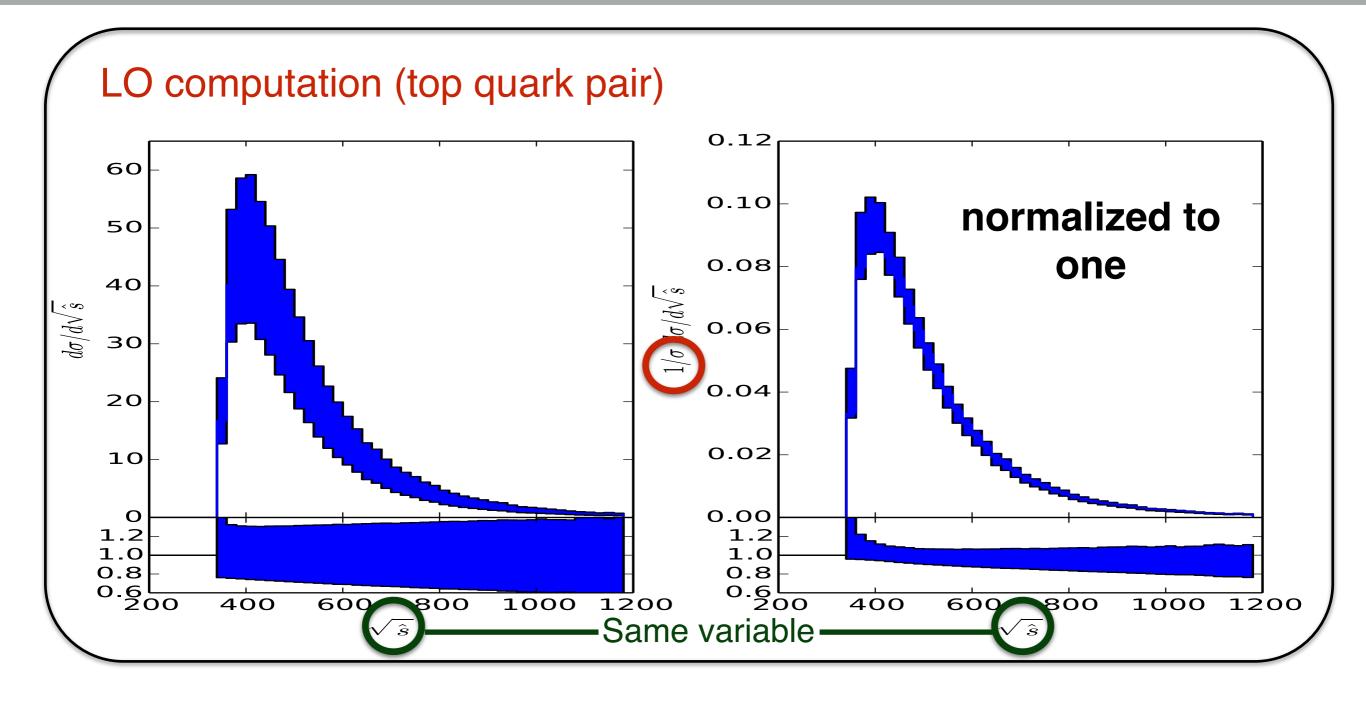
$$\hat{\sigma} = \sigma^{\text{Born}} \left(1 + \frac{\alpha_s}{2\pi} \sigma^{(1)} + \left(\frac{\alpha_s}{2\pi}\right)^2 \sigma^{(2)} + \left(\frac{\alpha_s}{2\pi}\right)^3 \sigma^{(3)} + \dots \right)$$

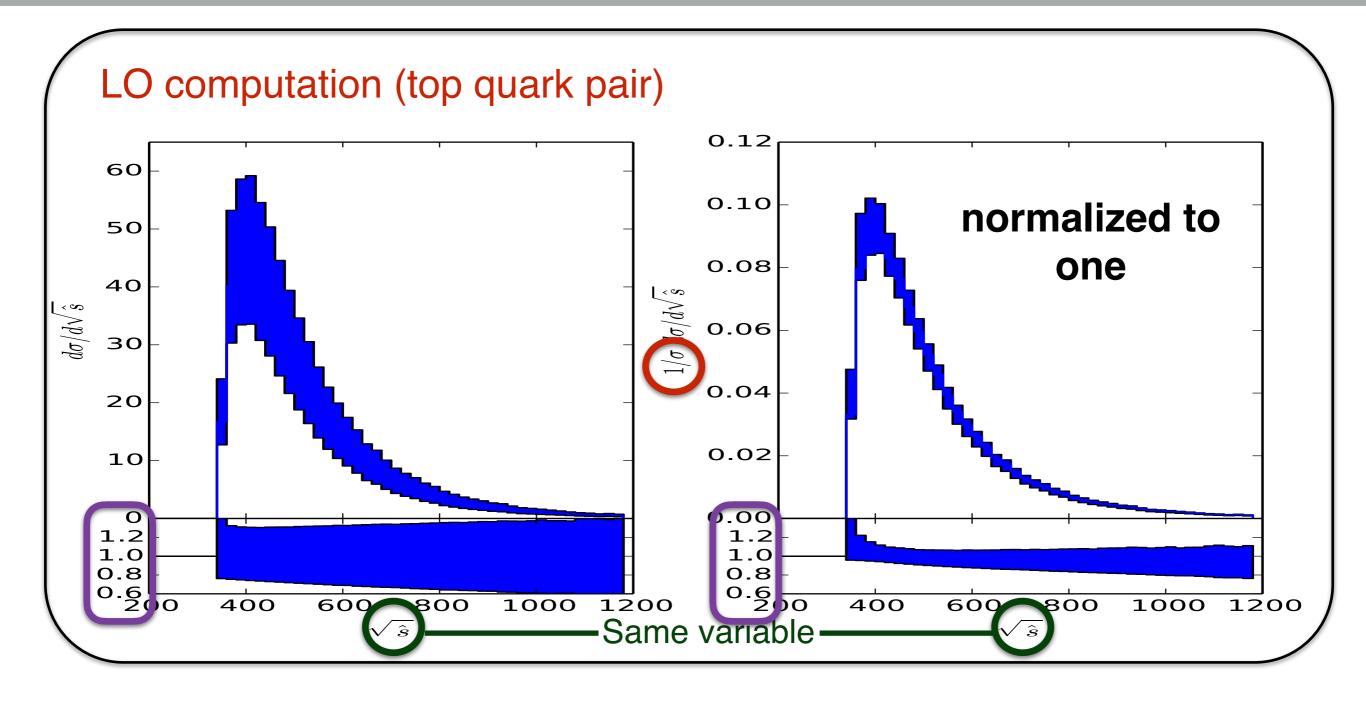
- Leading Order predictions can depend strongly on the renormalization and factorization scales
- Including higher order corrections reduces the dependence on these scales

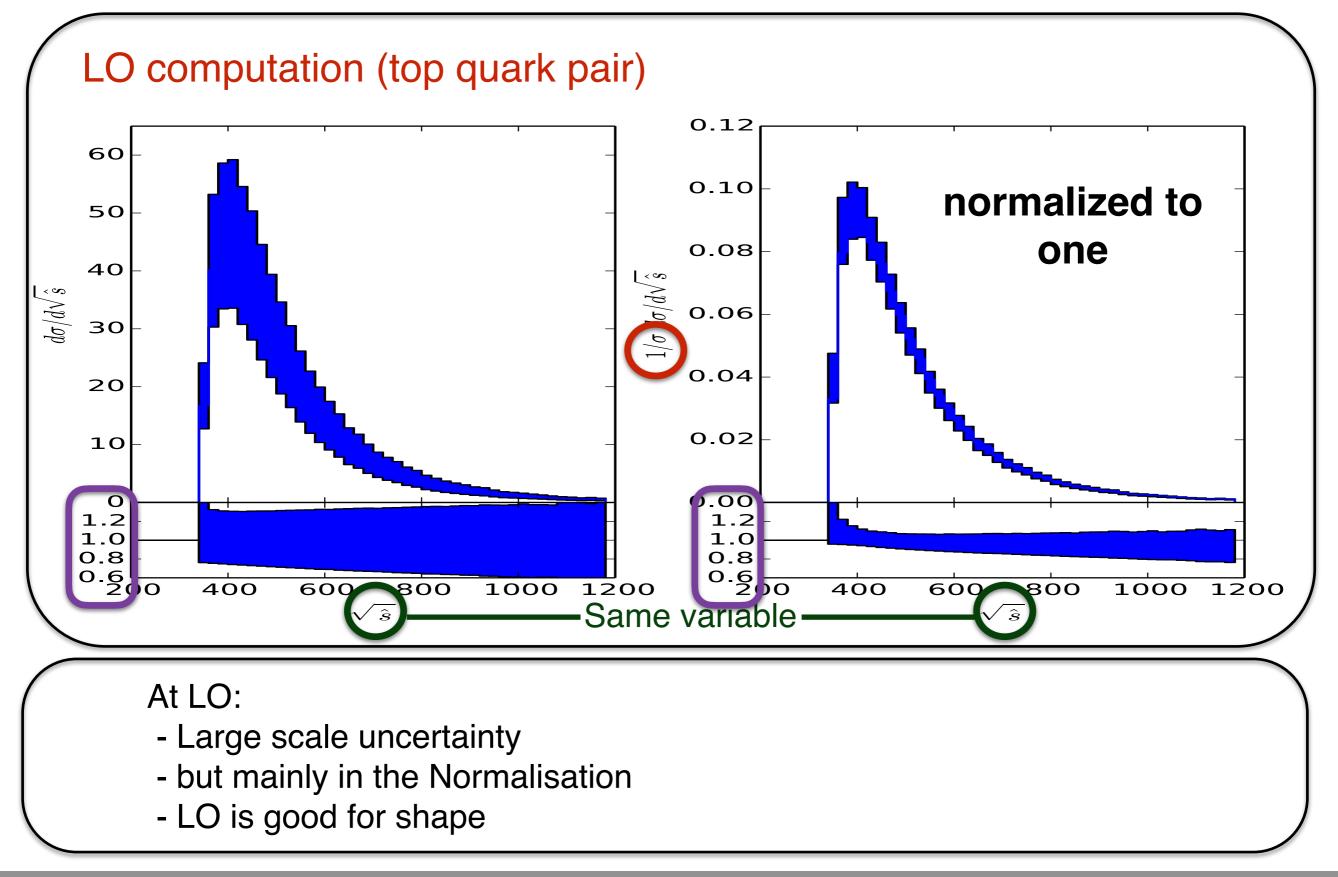












Question time



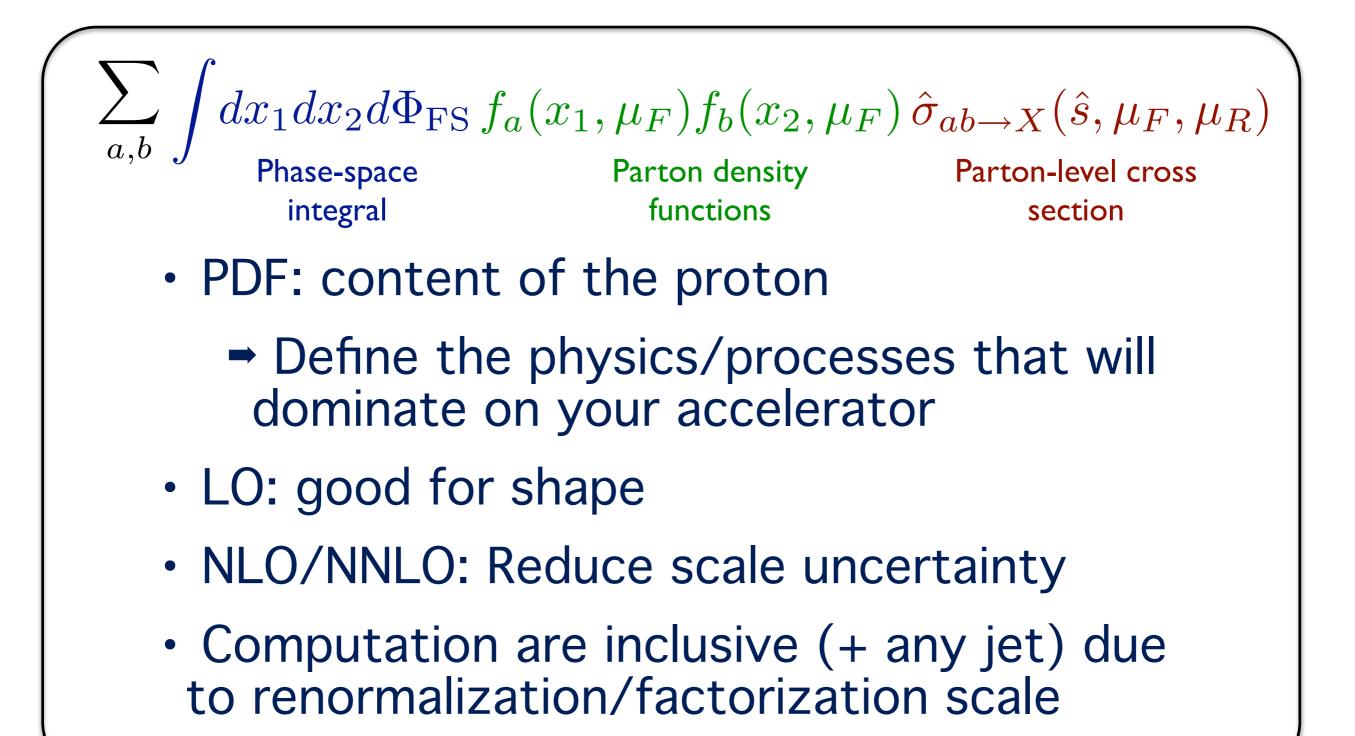
Allez sur wooclap.com

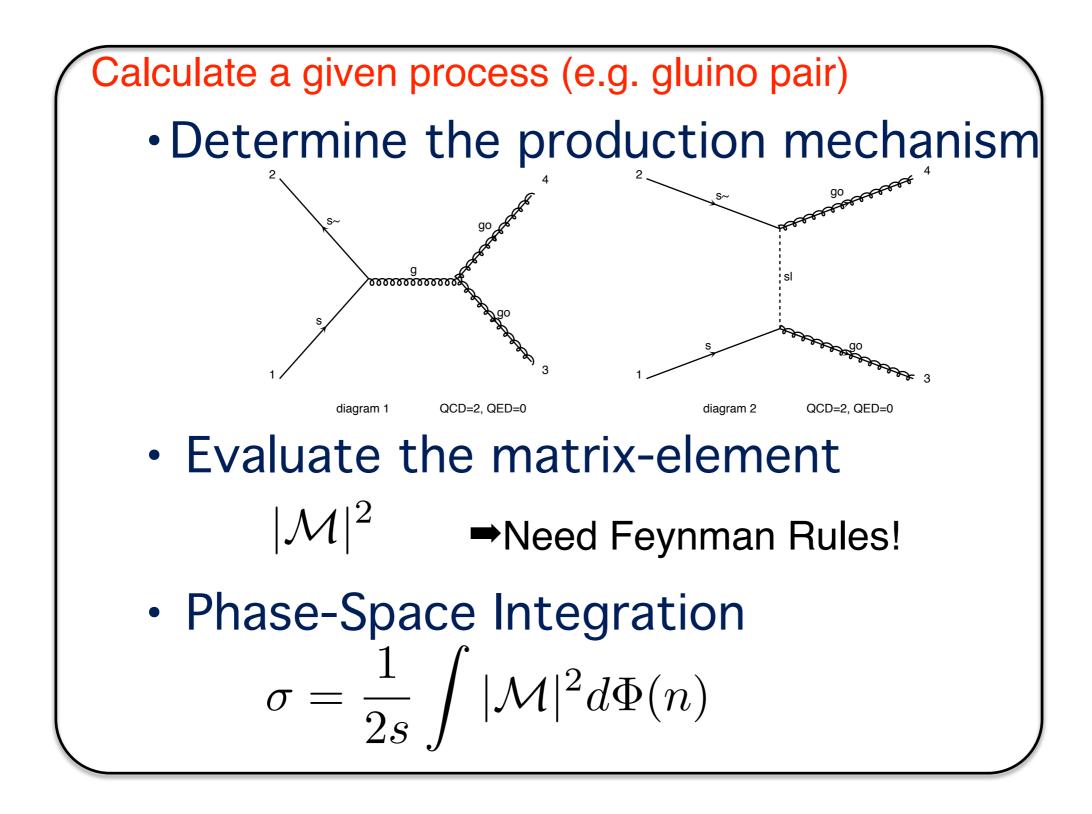
Entrez le code d'événement dans le bandeau supérieur

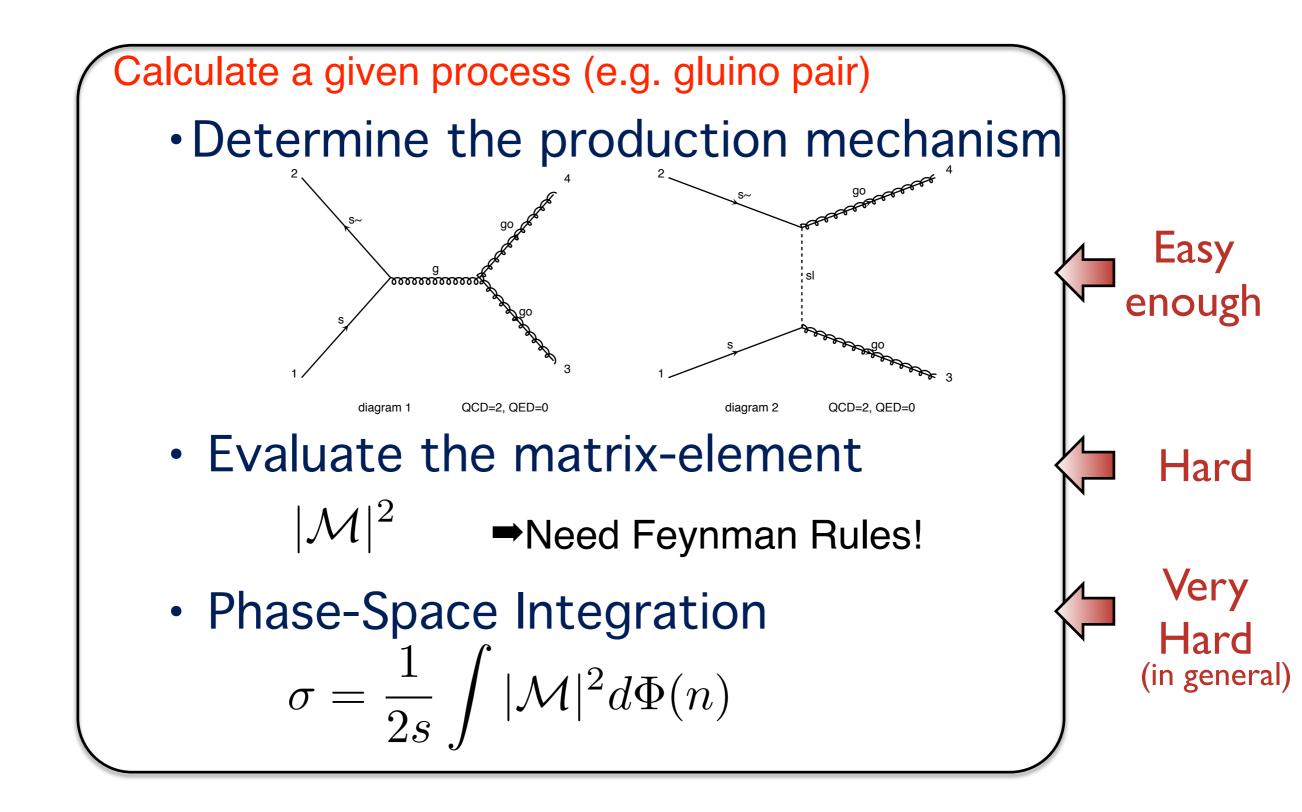
Code d'événement MADGRAPH

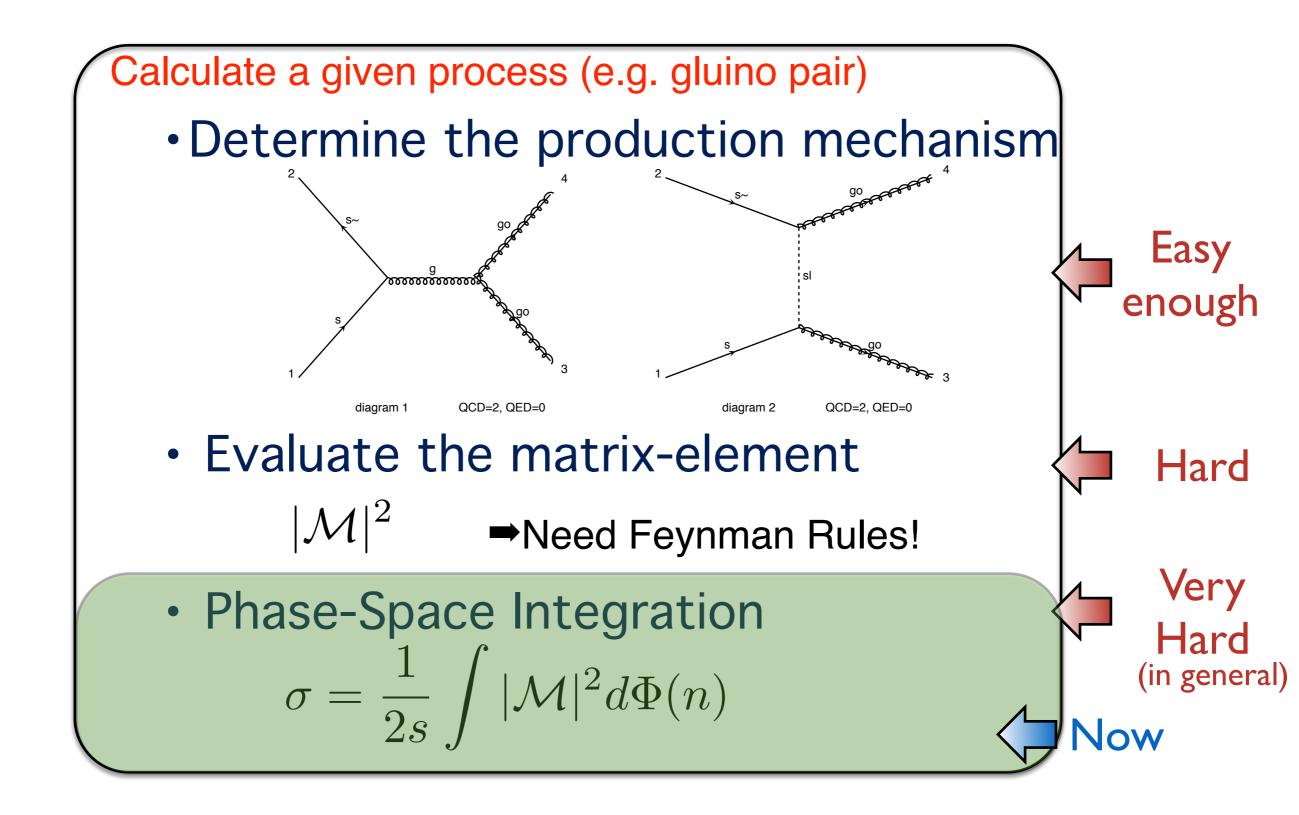
Activer les réponses par SMS

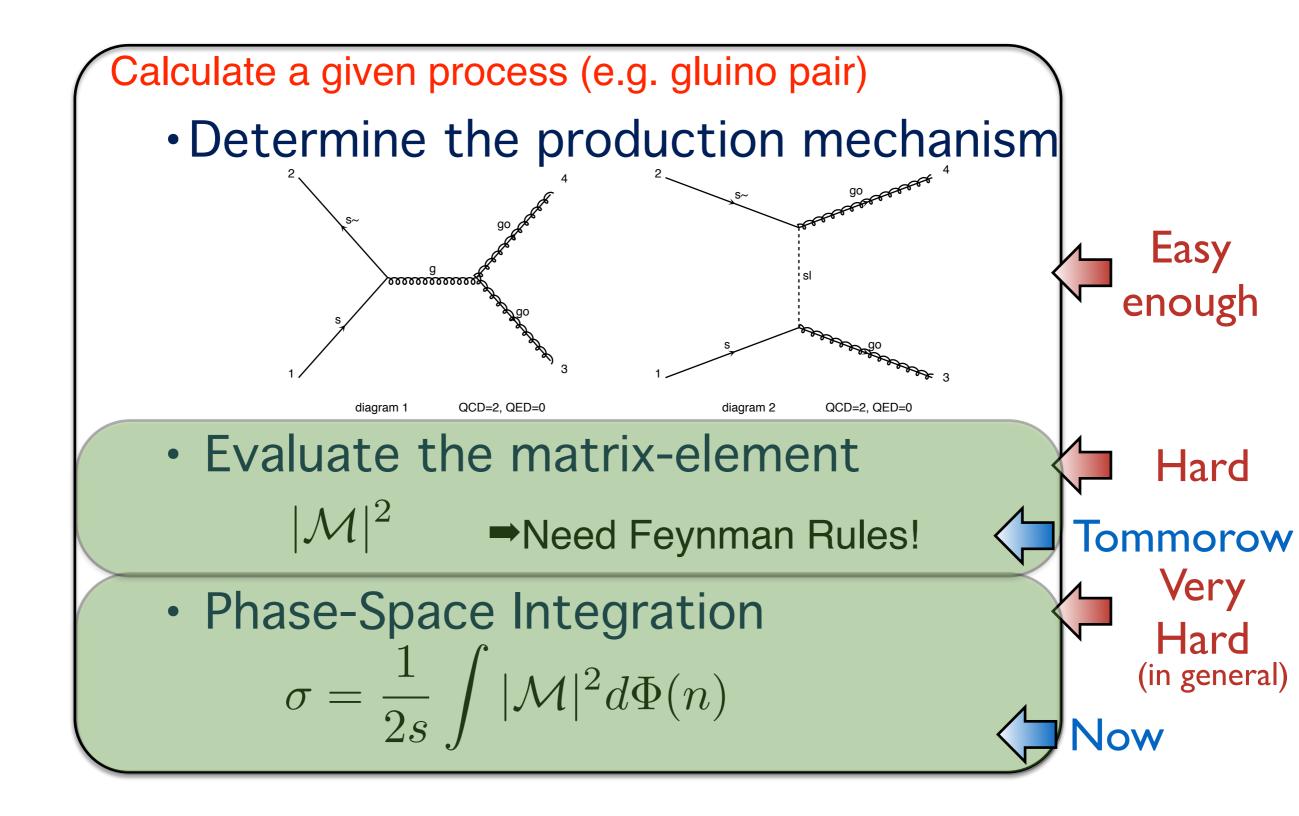
To Remember











Monte Carlo Integration

Calculations of cross section or decay widths involve integrations over high-dimension phase space of very peaked functions:

$$\sigma = \frac{1}{2s} \int |\mathcal{M}|^2 d\Phi(n)$$

Calculations of cross section or decay widths involve integrations over high-dimension phase space of very peaked functions:

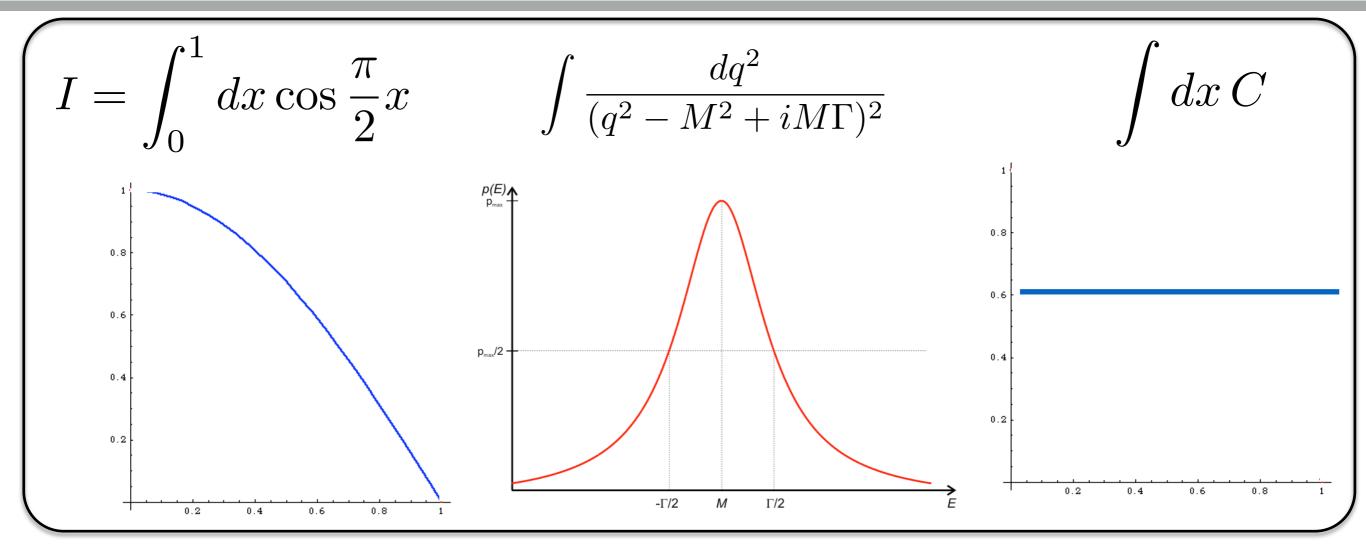
Calculations of cross section or decay widths involve integrations over high-dimension phase space of very peaked functions:

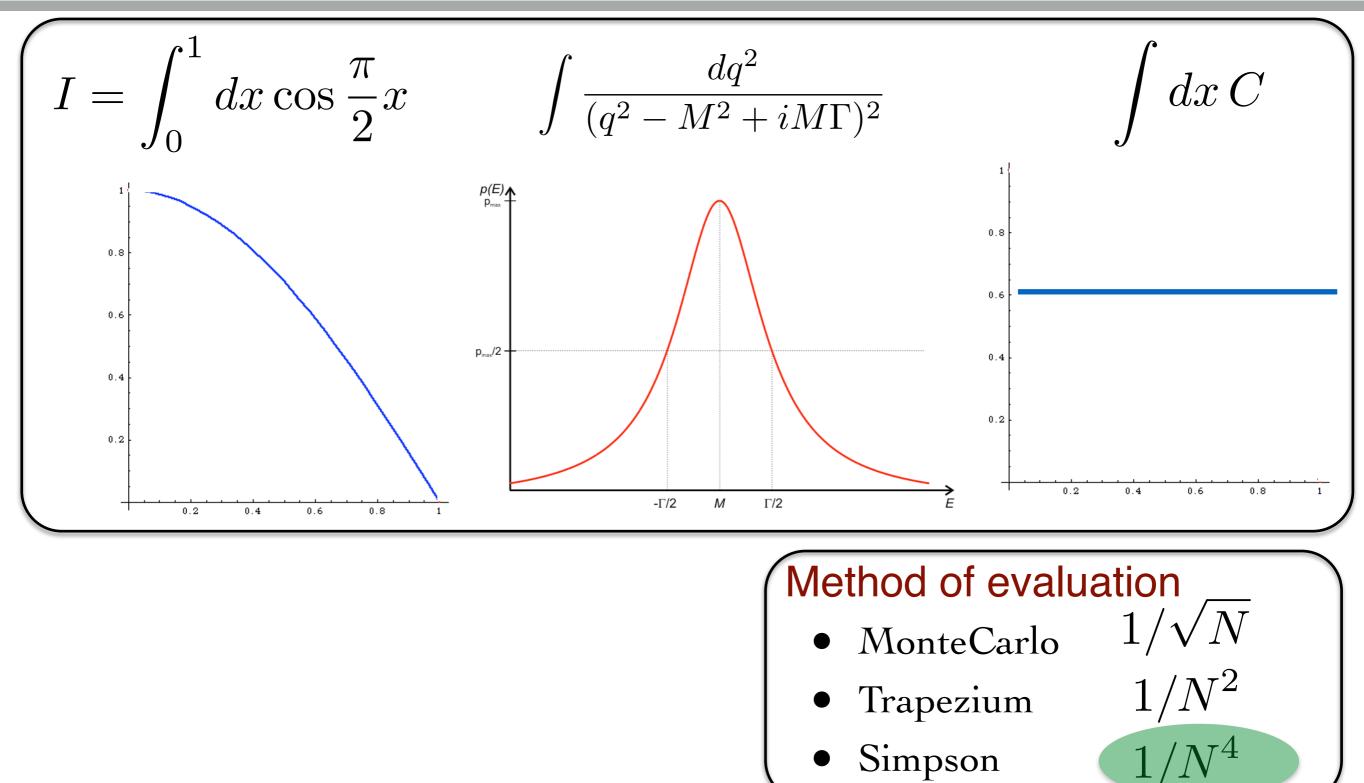
General and flexible method is needed

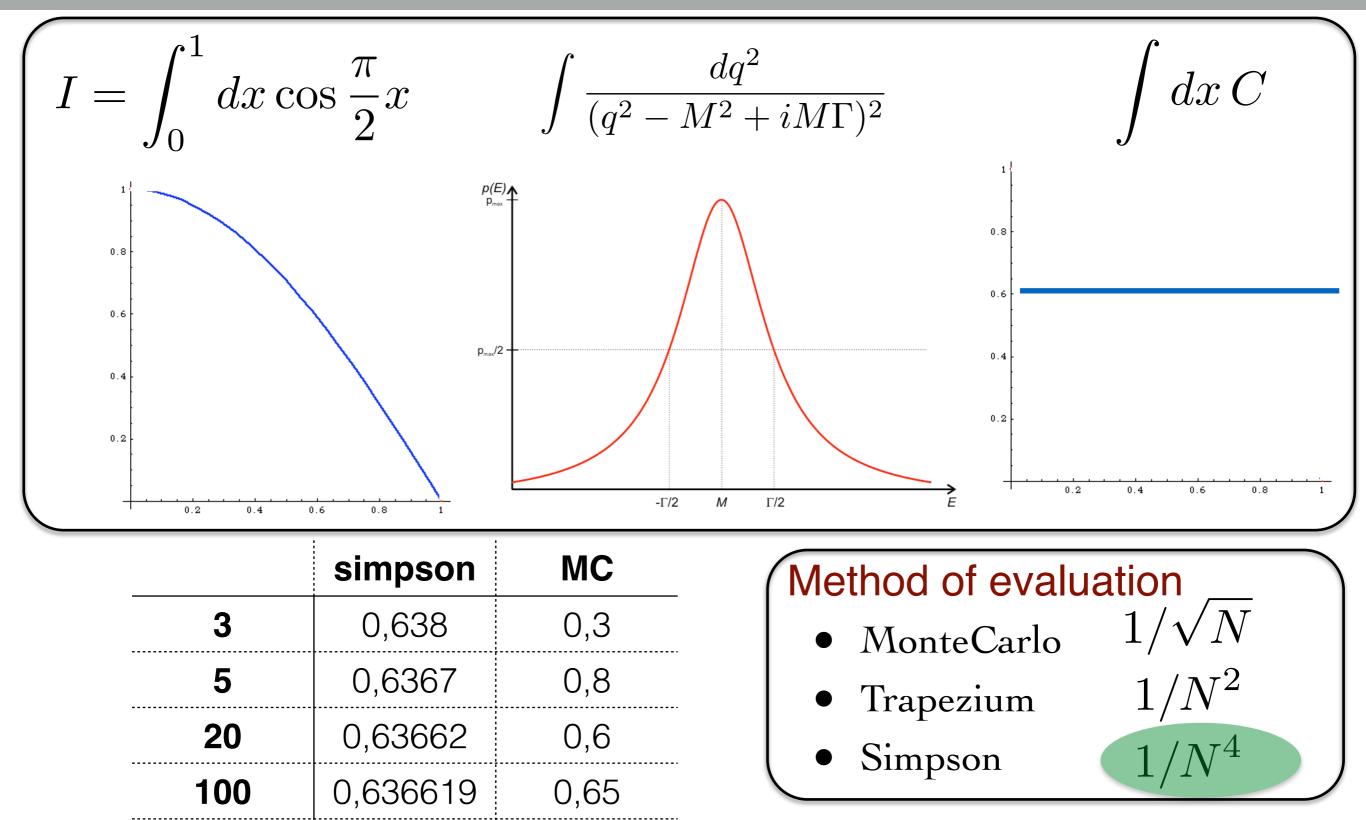
Calculations of cross section or decay widths involve integrations over high-dimension phase space of very peaked functions:

General and flexible method is needed

Not only integrating but also generates events







1000

0,636619

0,636

Question time

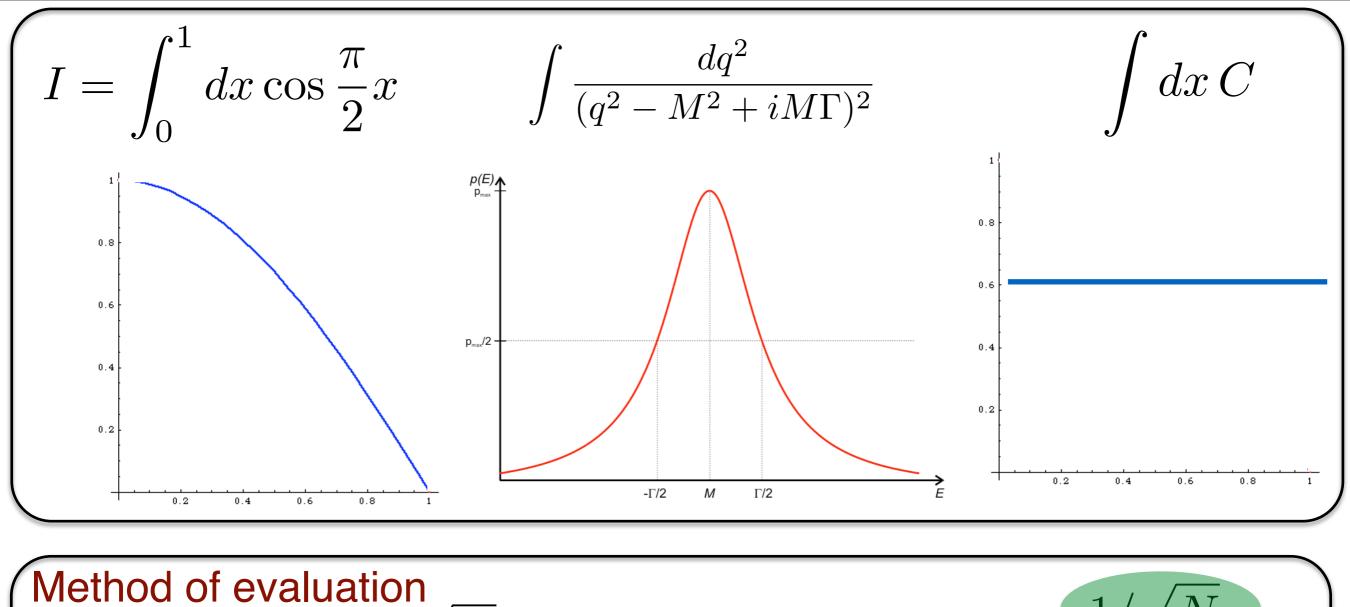


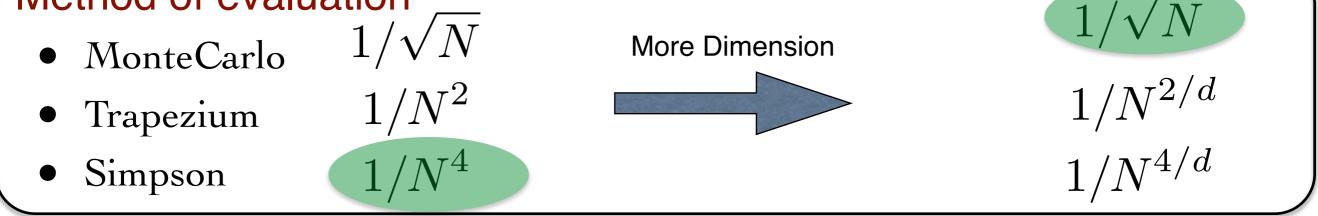
Allez sur wooclap.com

Entrez le code d'événement dans le bandeau supérieur

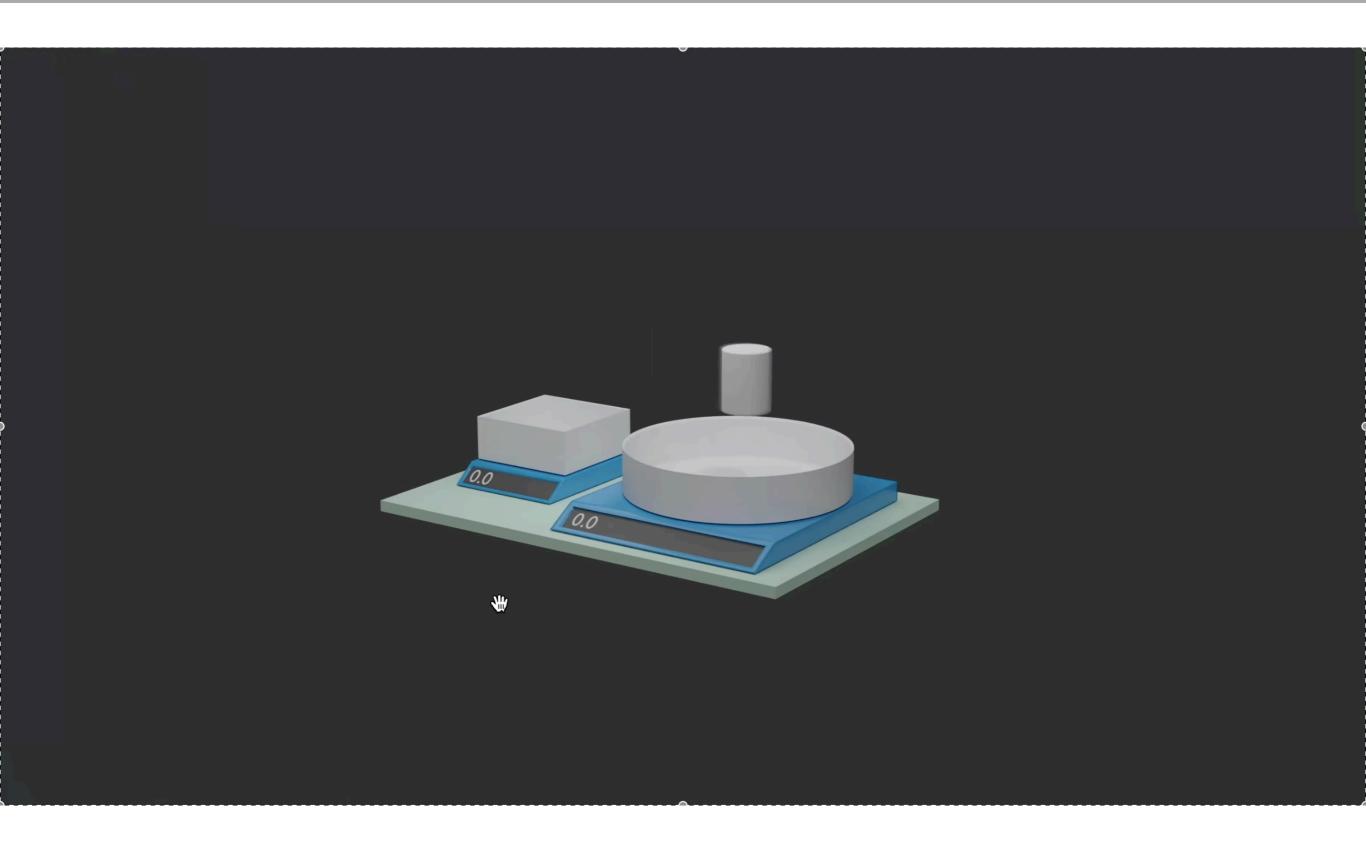
Code d'événement MADGRAPH

Activer les réponses par SMS

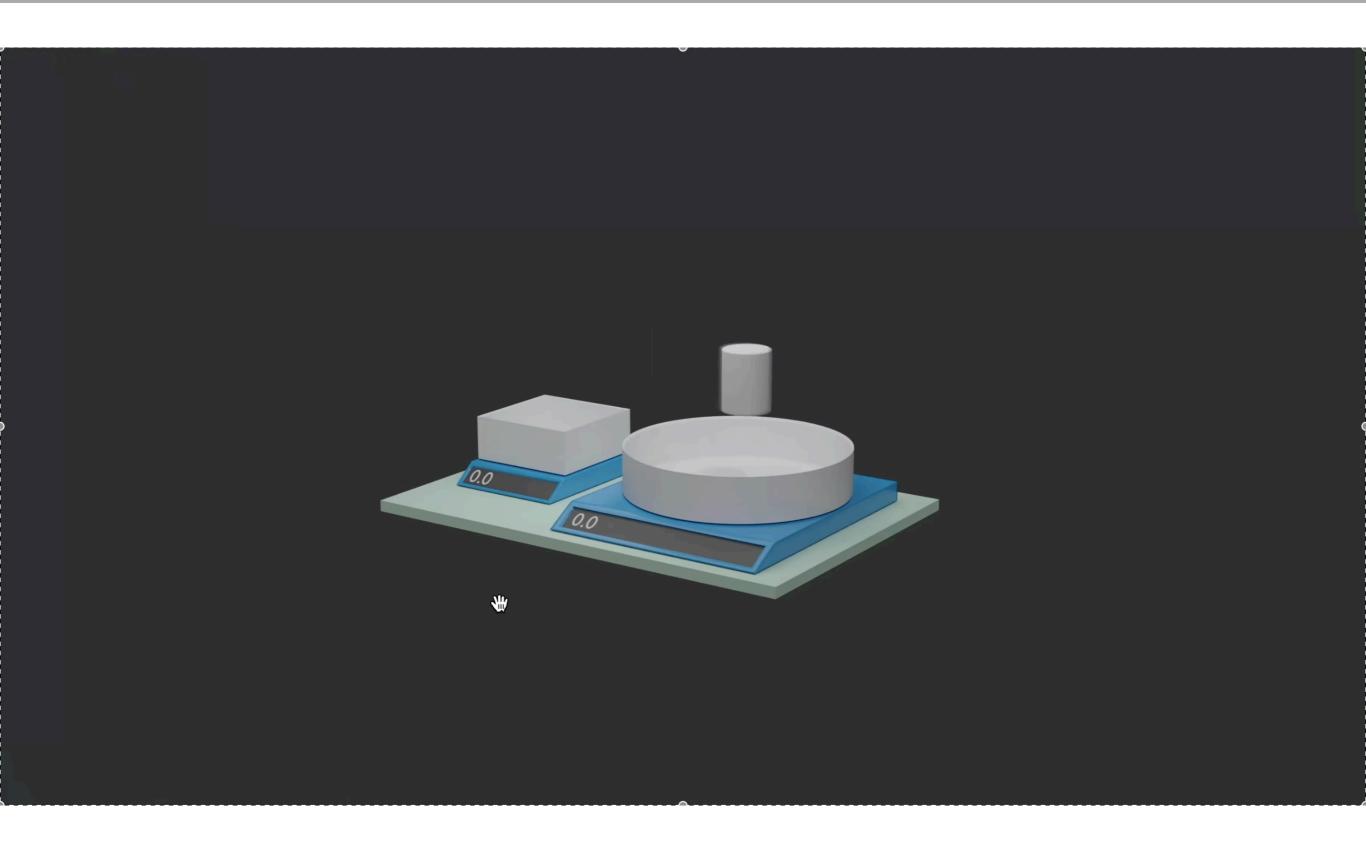




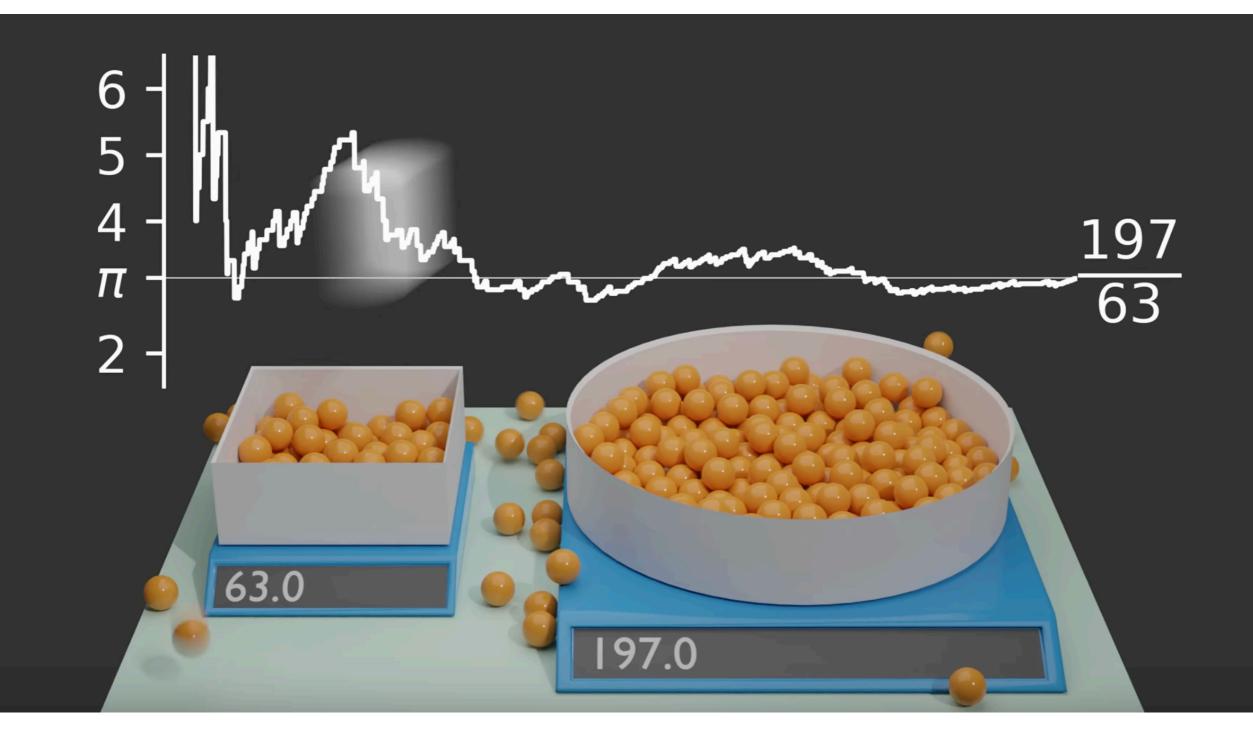
Monte-Carlo

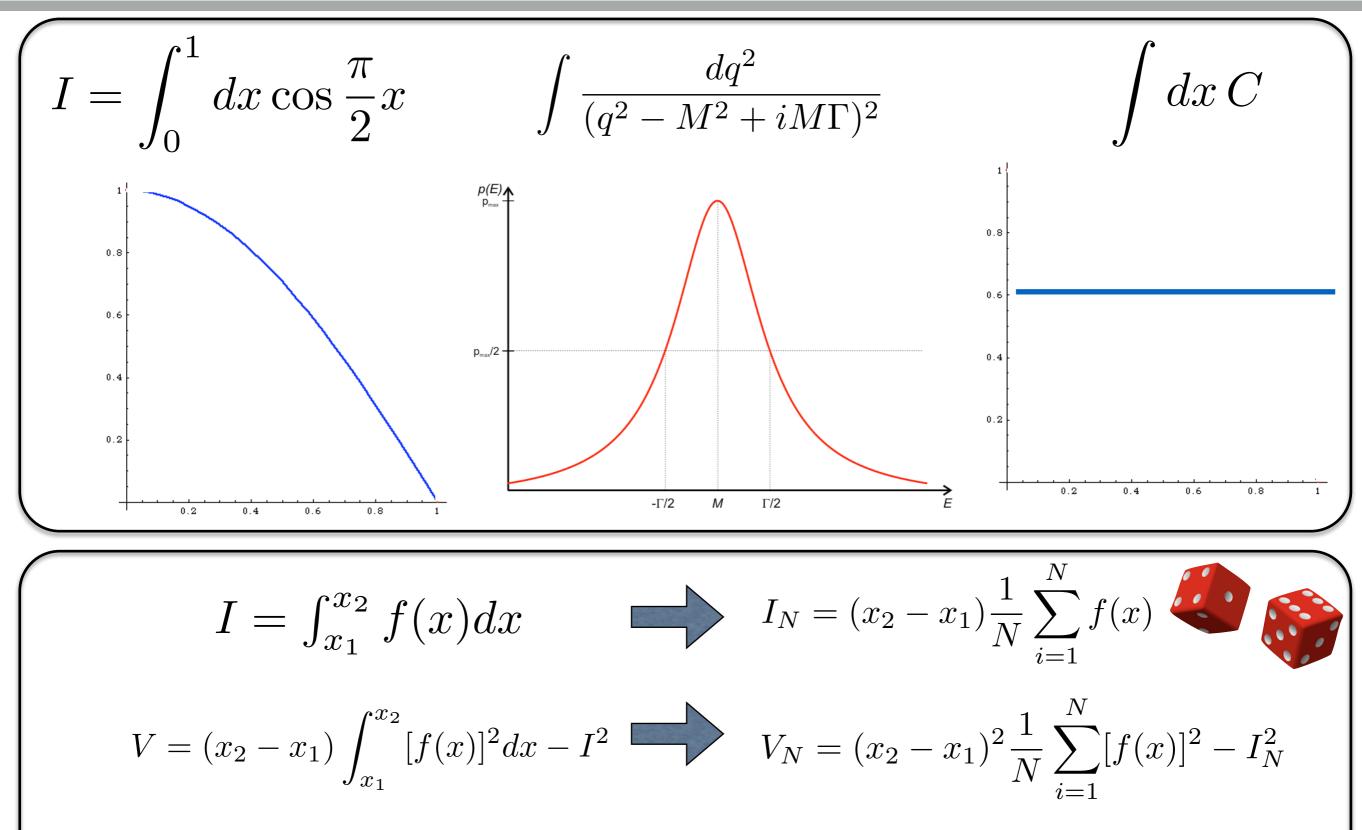


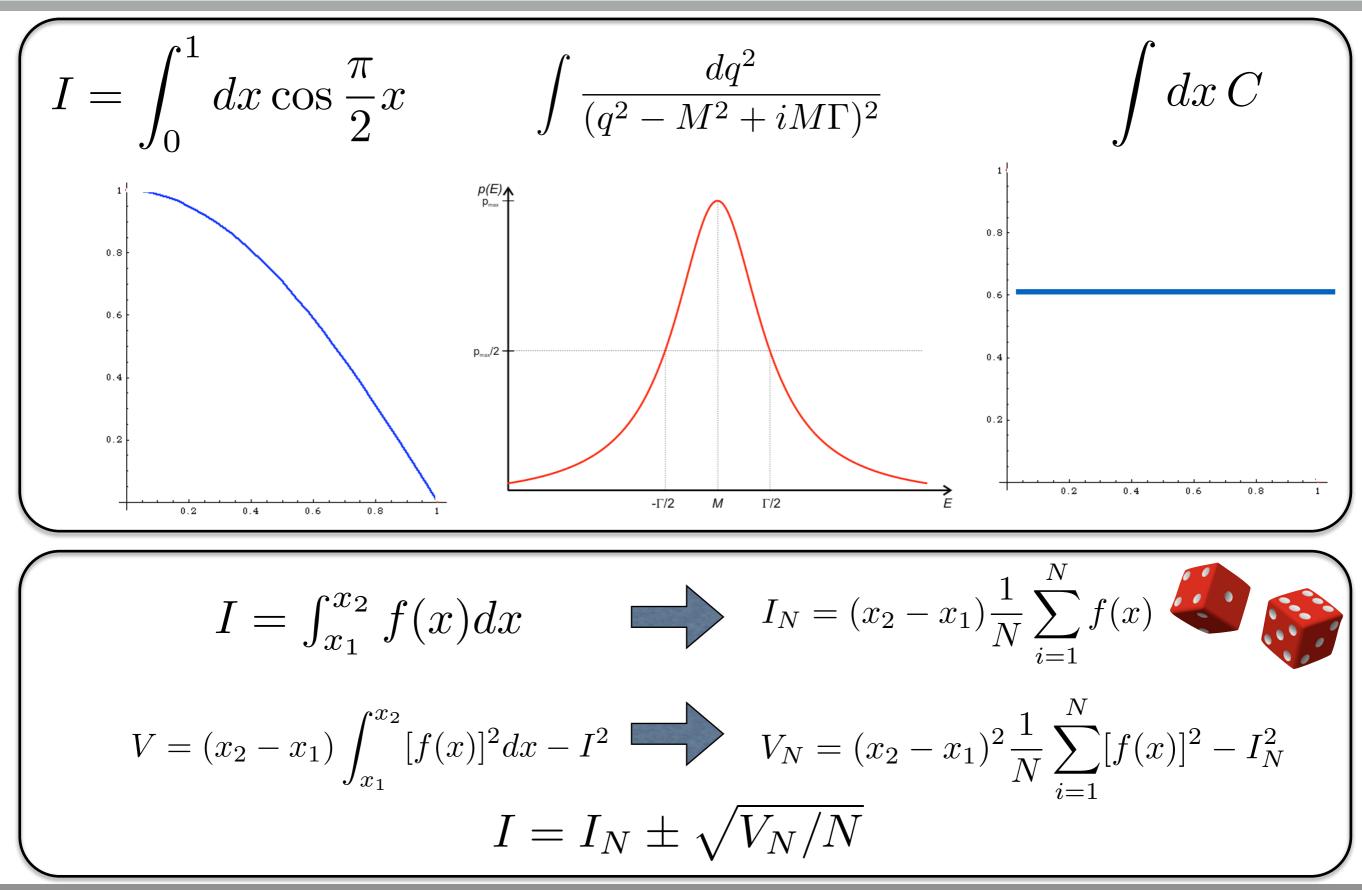
Monte-Carlo

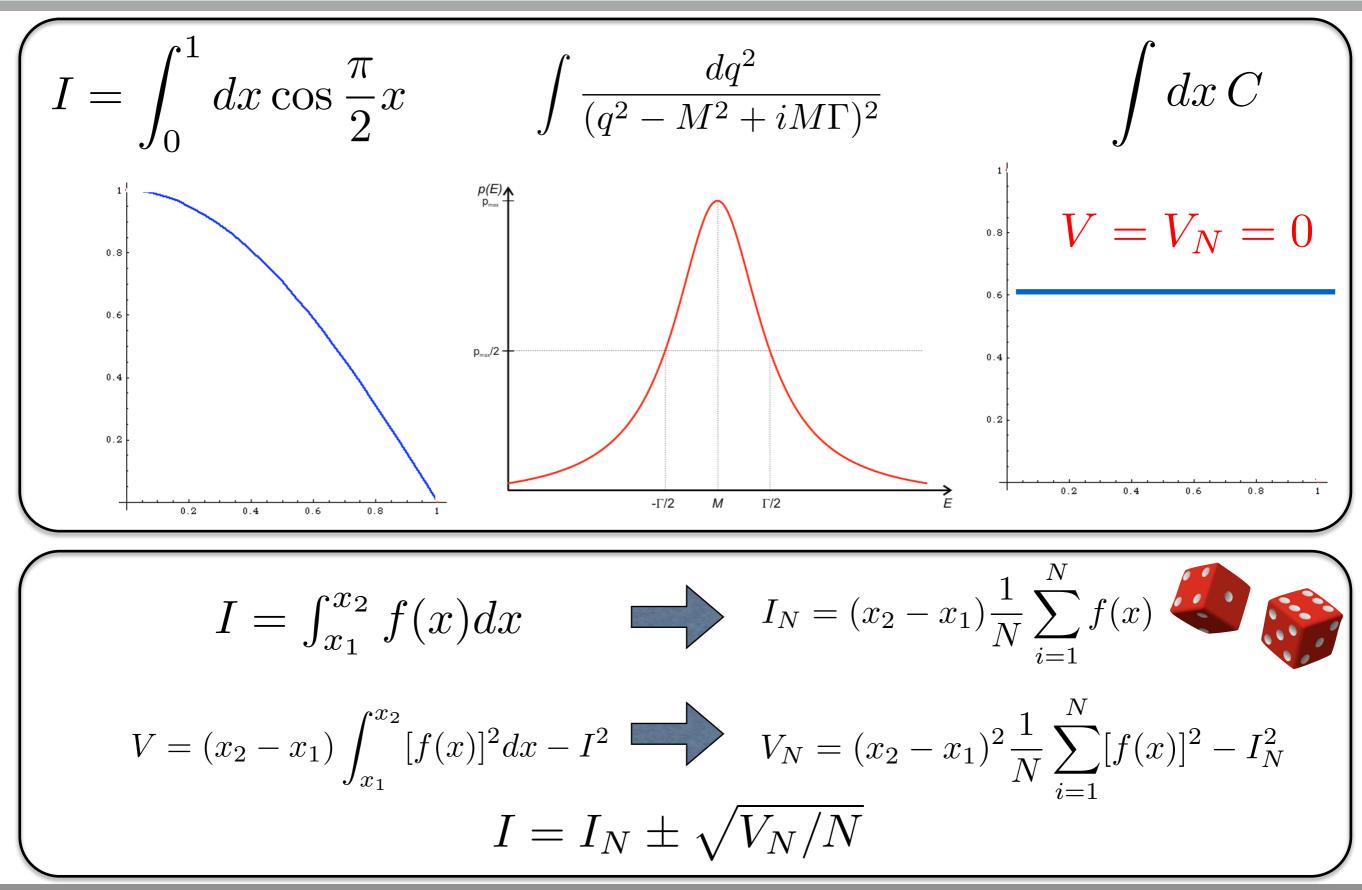


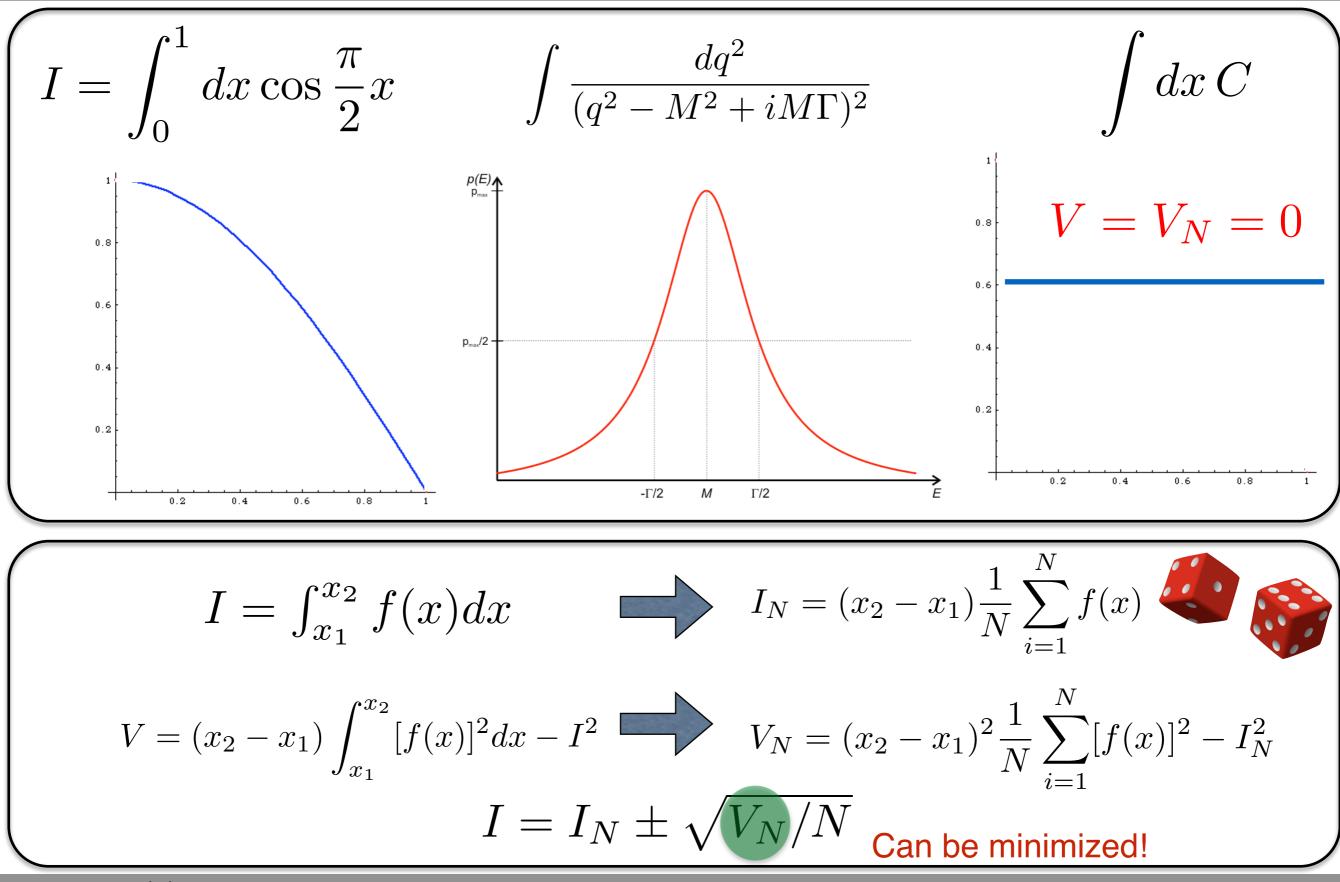
Monte-Carlo





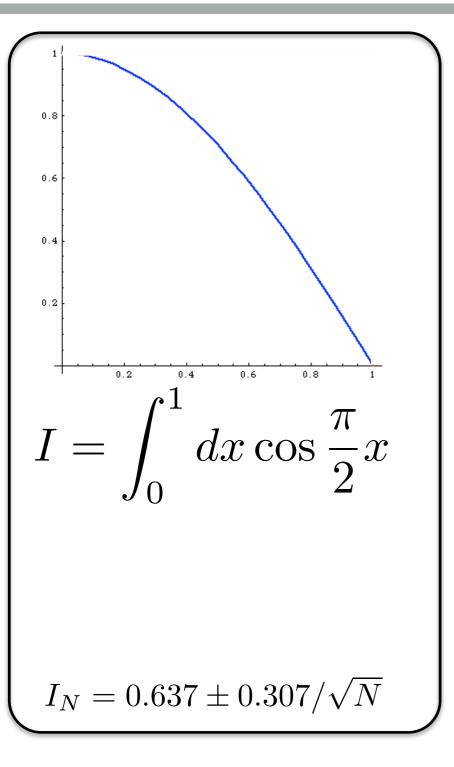


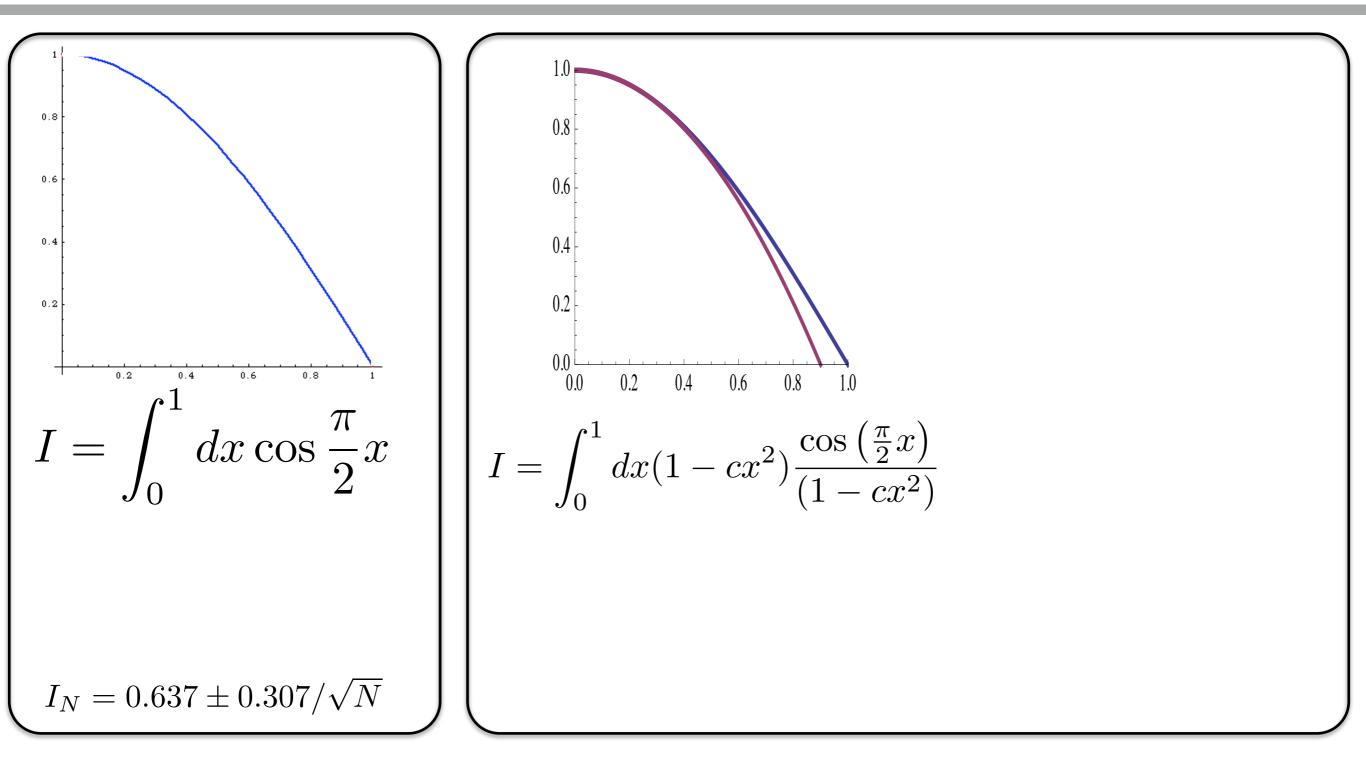


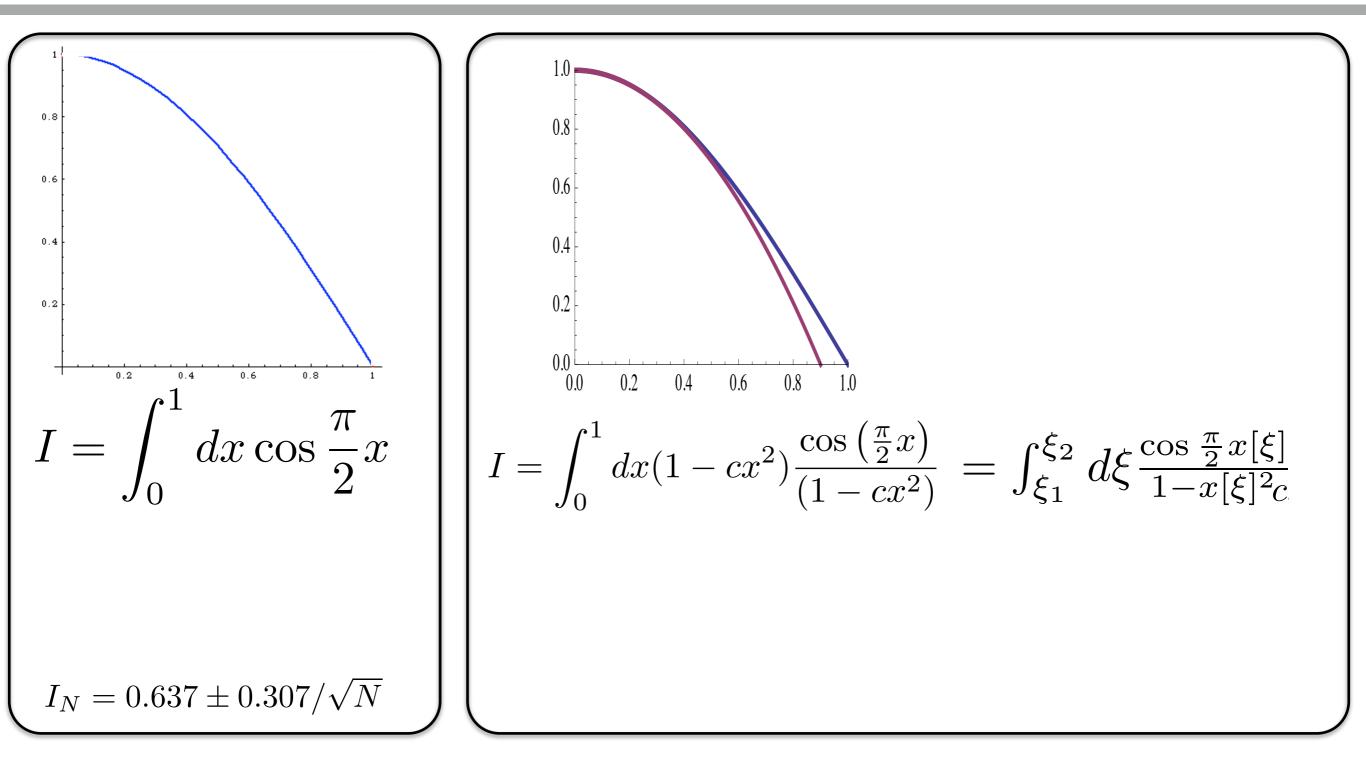


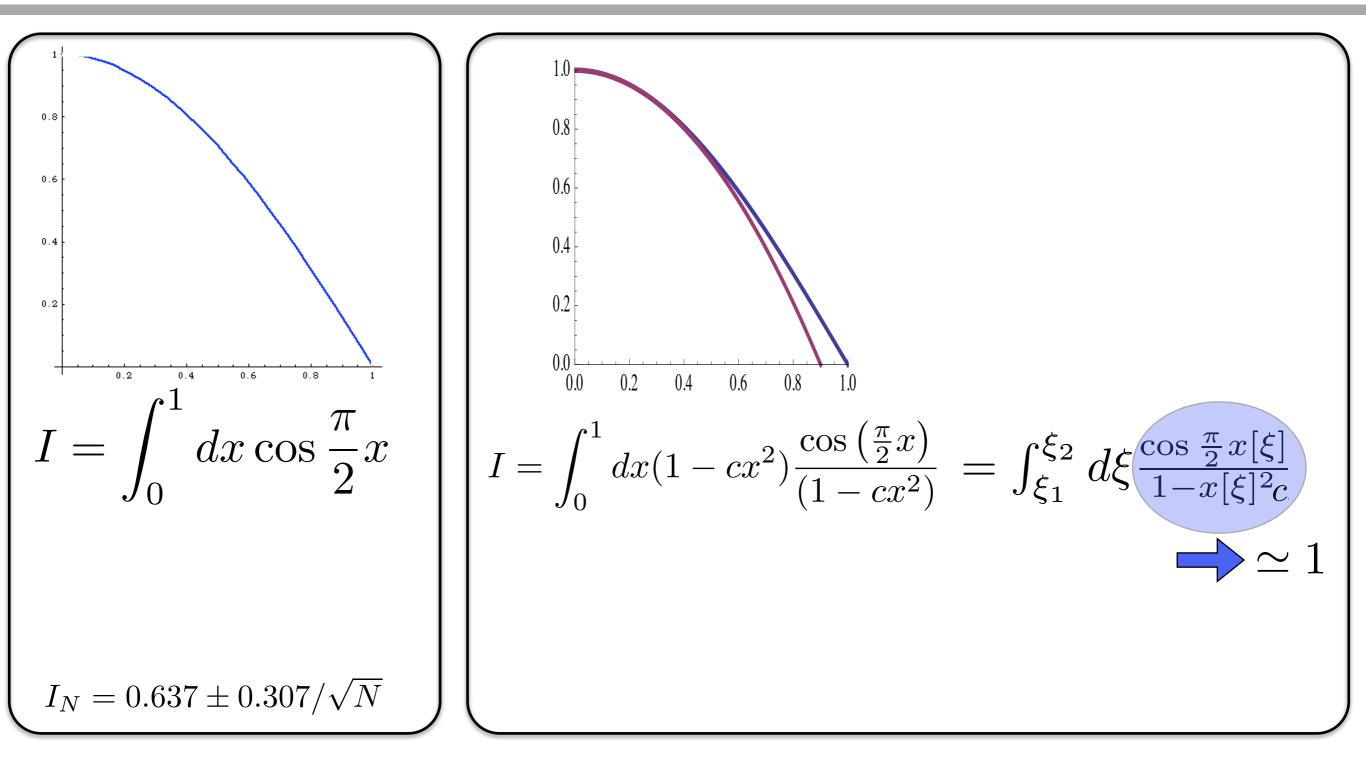
Mattelaer Olívíer

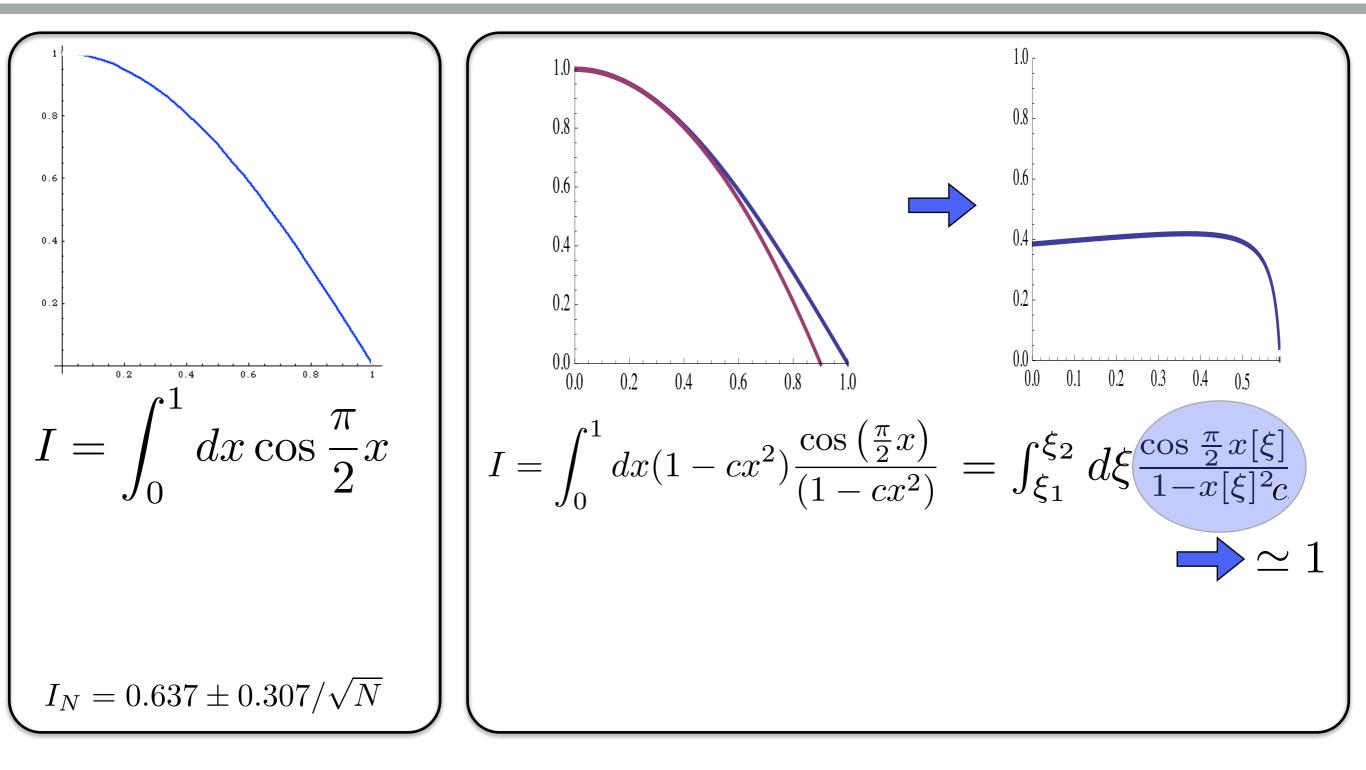
Japan 2023

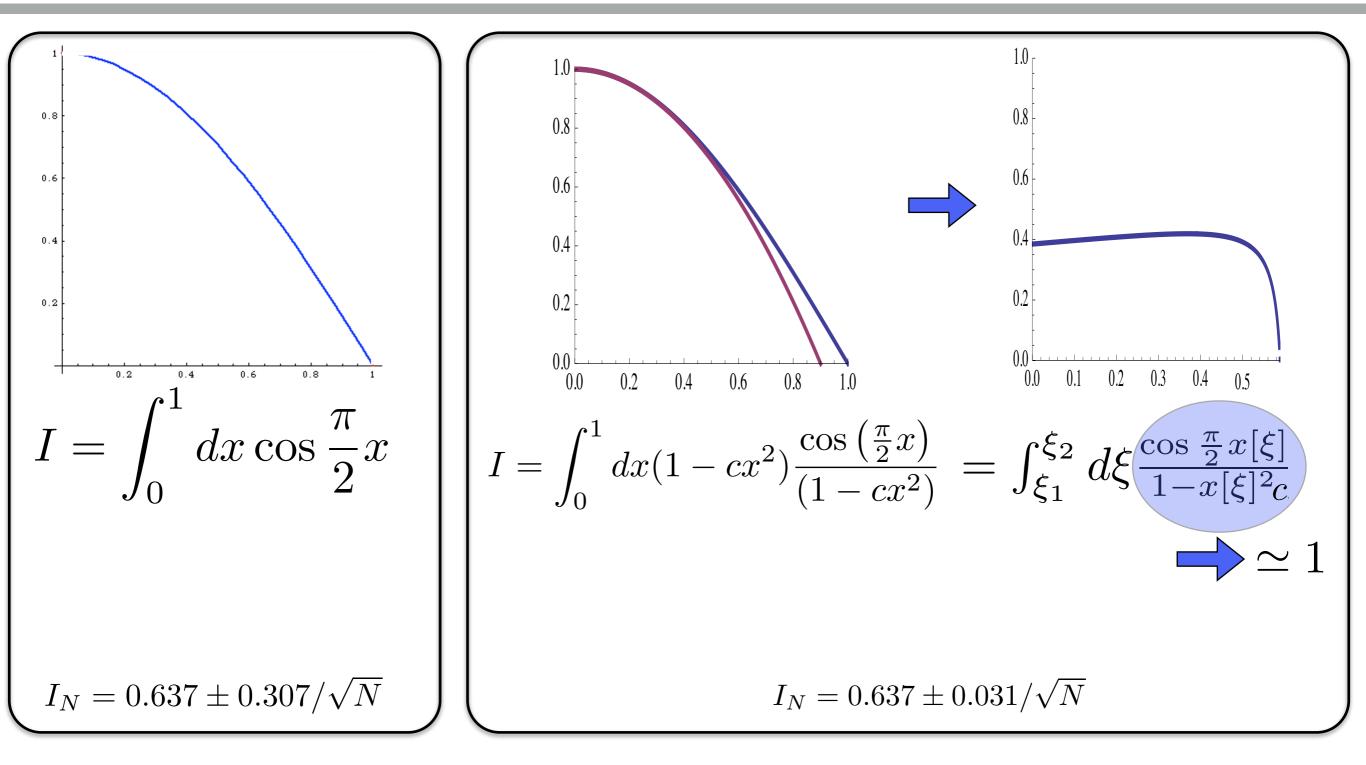


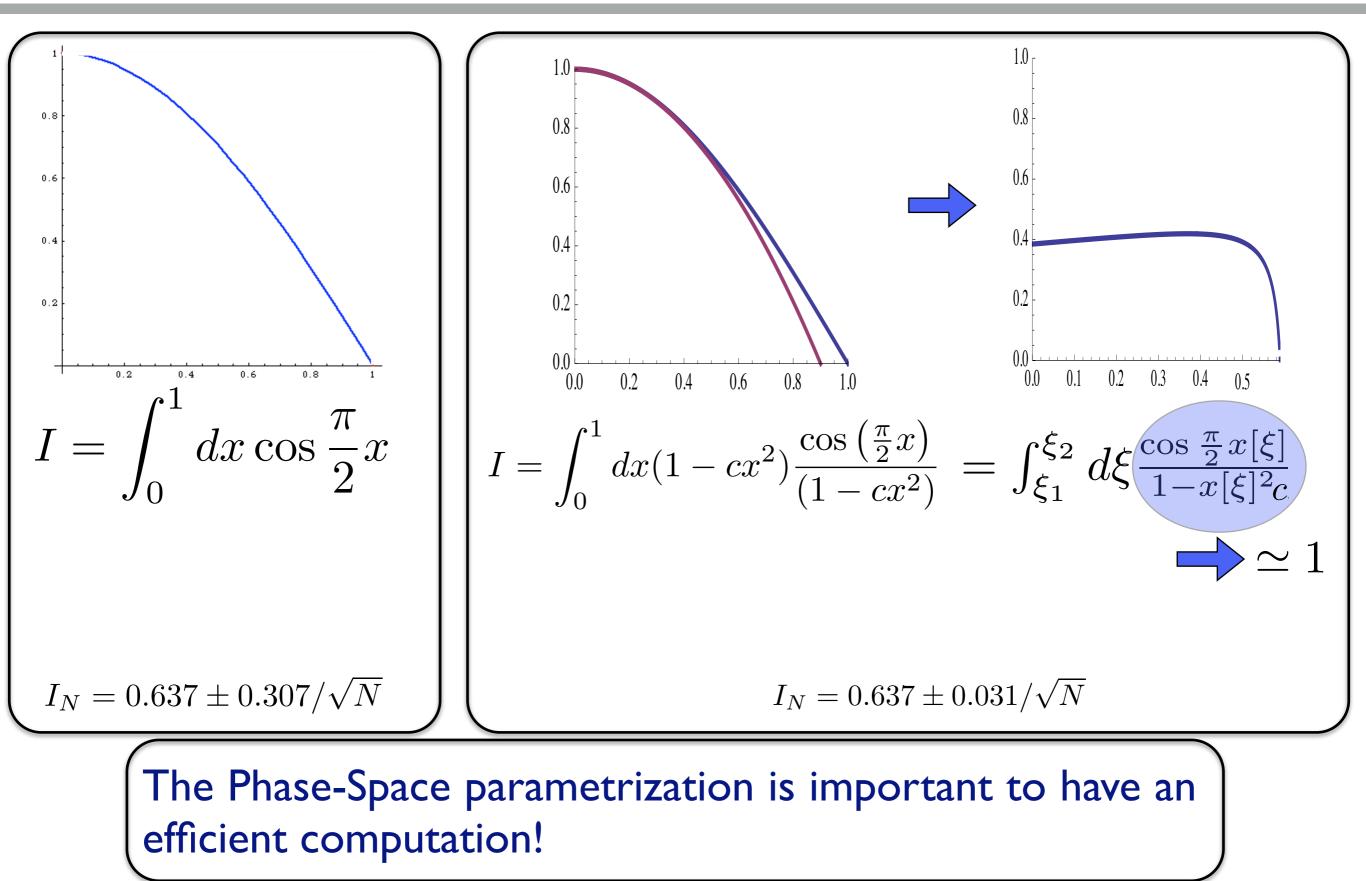


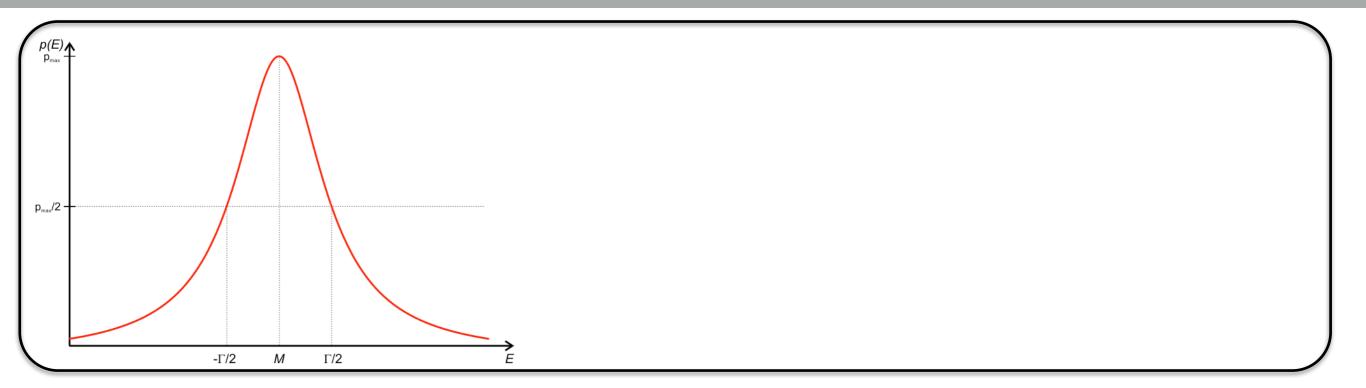


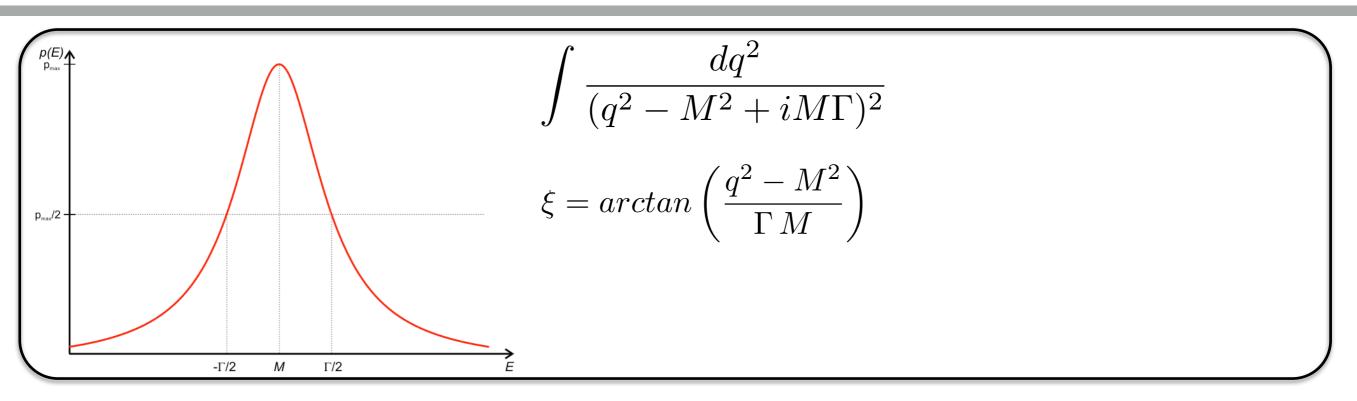


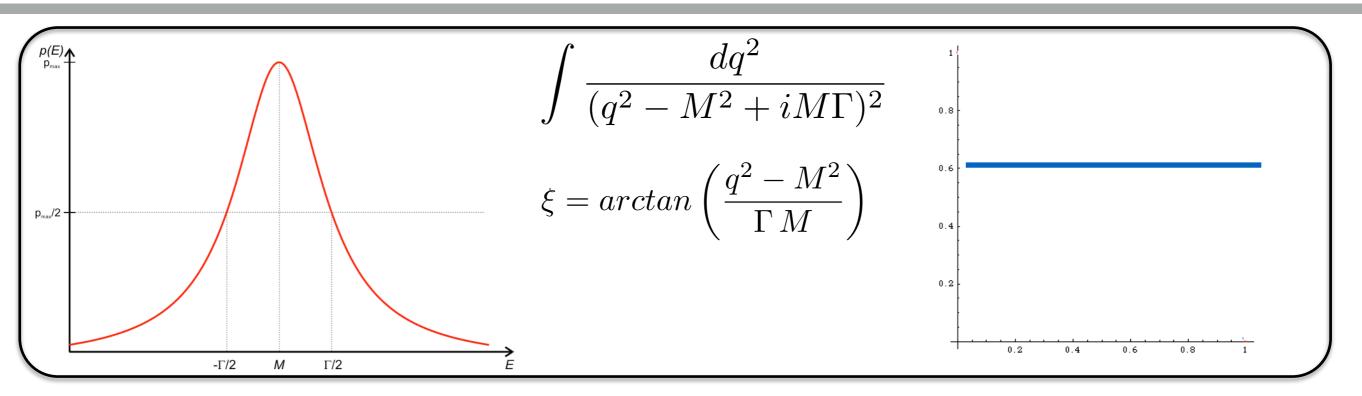




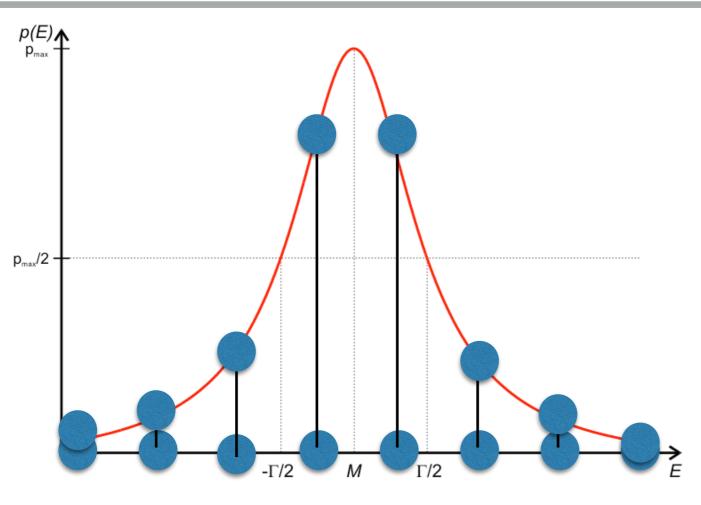








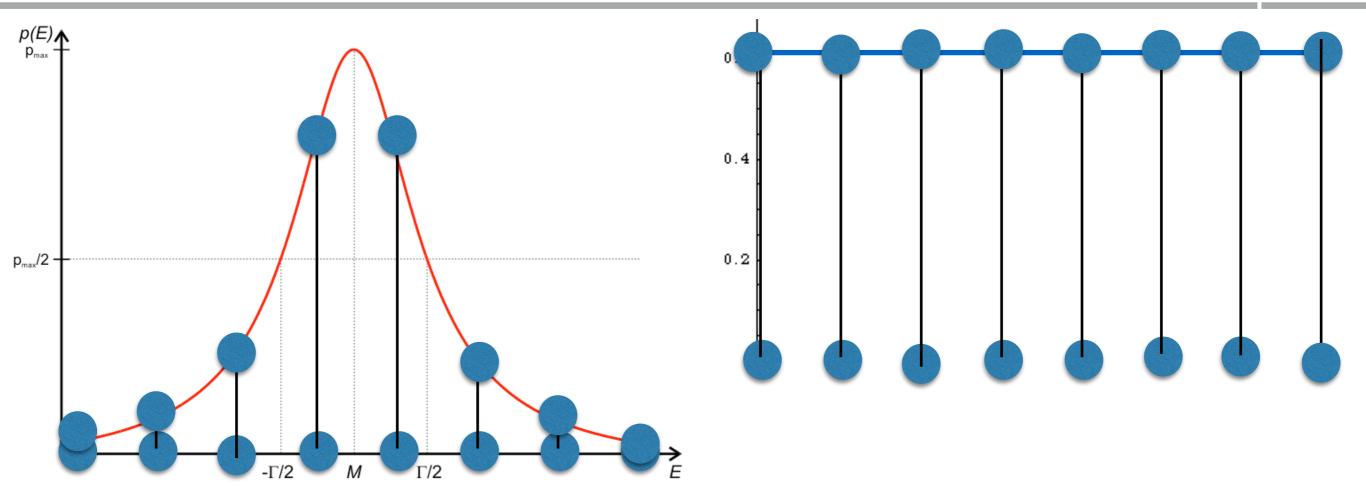
Why importance?



Why Importance Sampling?

We probe more often the region where the function is high!

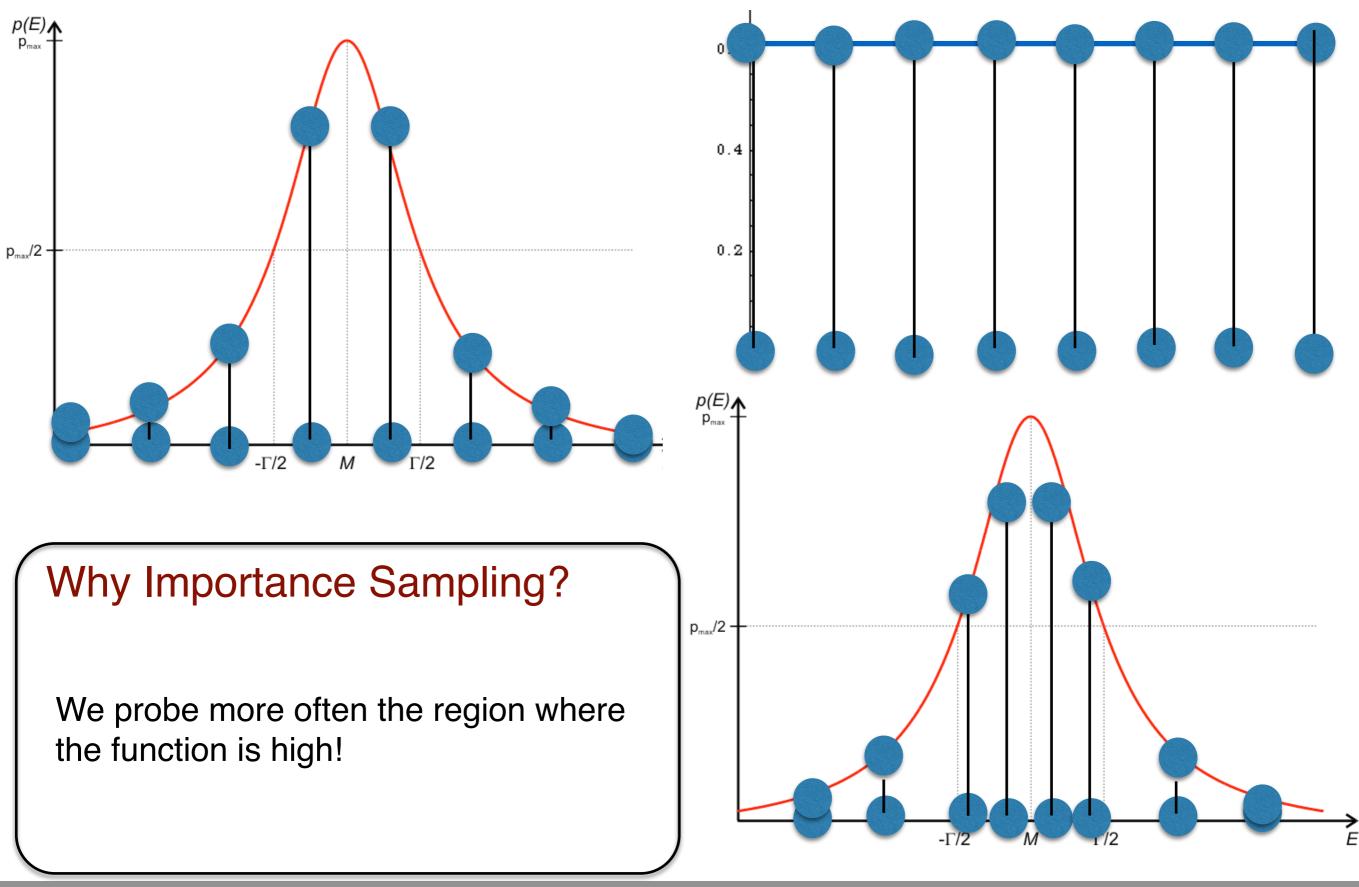
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Why importance?



Question time



Allez sur wooclap.com

Entrez le code d'événement dans le bandeau supérieur

Code d'événement MADGRAPH

Activer les réponses par SMS

Key Point

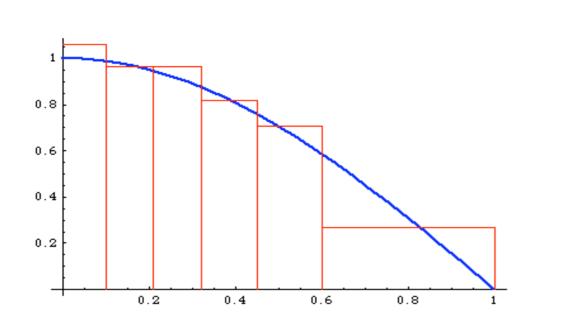
- Generate the random point in a distribution which is close to the function to integrate.
- This is a change of variable, such that the function is flatter in this new variable.
- Needs to know an approximate function.

Adaptative Monte-Carlo

 Create an approximation of the function on the flight!

Adaptative Monte-Carlo

 Create an approximation of the function on the flight!



Algorithm

- 1. Creates bin such that each of them have the same contribution.
 - Many bins where the function is large

2. Use the approximate for the importance sampling method.

More than one Dimension

• VEGAS works only with 1(few) dimension

memory problem

More than one Dimension

- VEGAS works only with 1(few) dimension
 - memory problem

Solution

•Use projection on the axis

 $\vec{p}(x) = p(x) \cdot p(y) \cdot p(z) \dots$

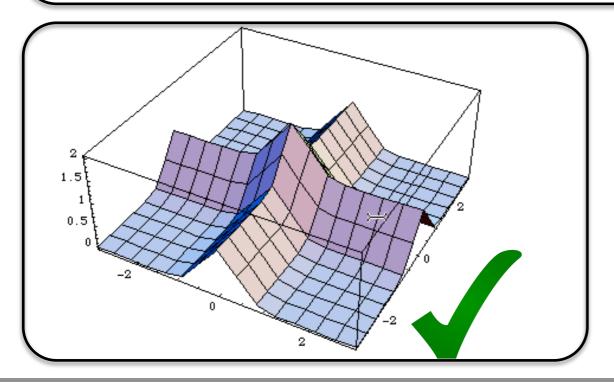
More than one Dimension

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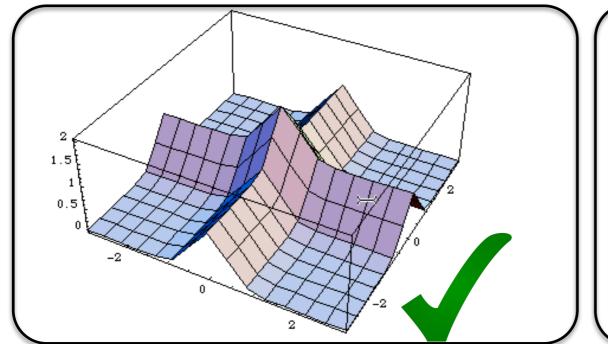
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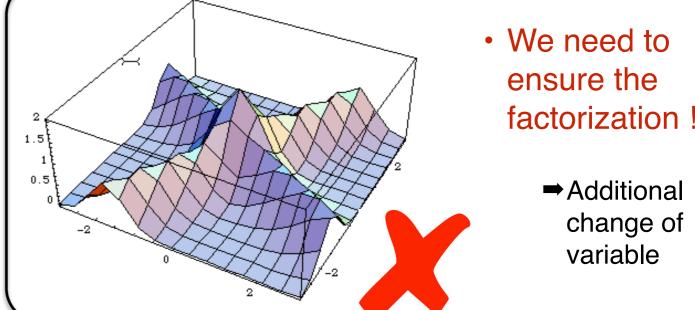
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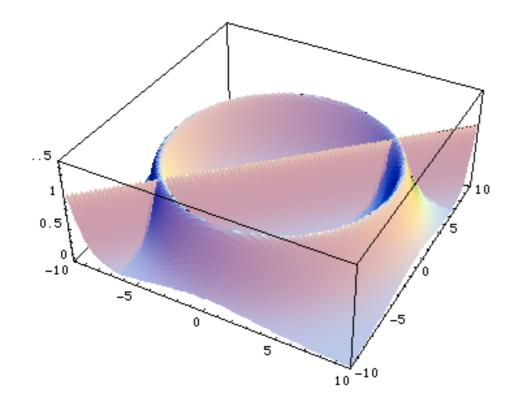
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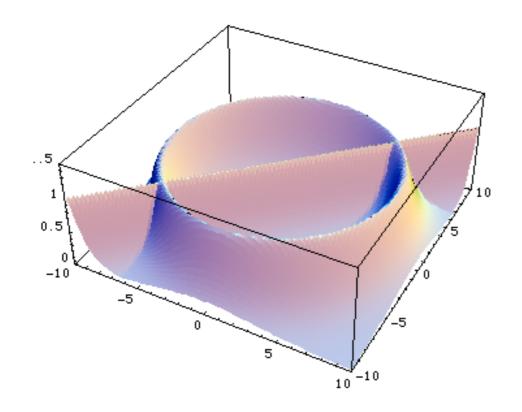


Multi-channel



What do we do if there is no transformation that aligns all integrand peaks to the chosen axes? Vegas is bound to fail!

Multi-channel



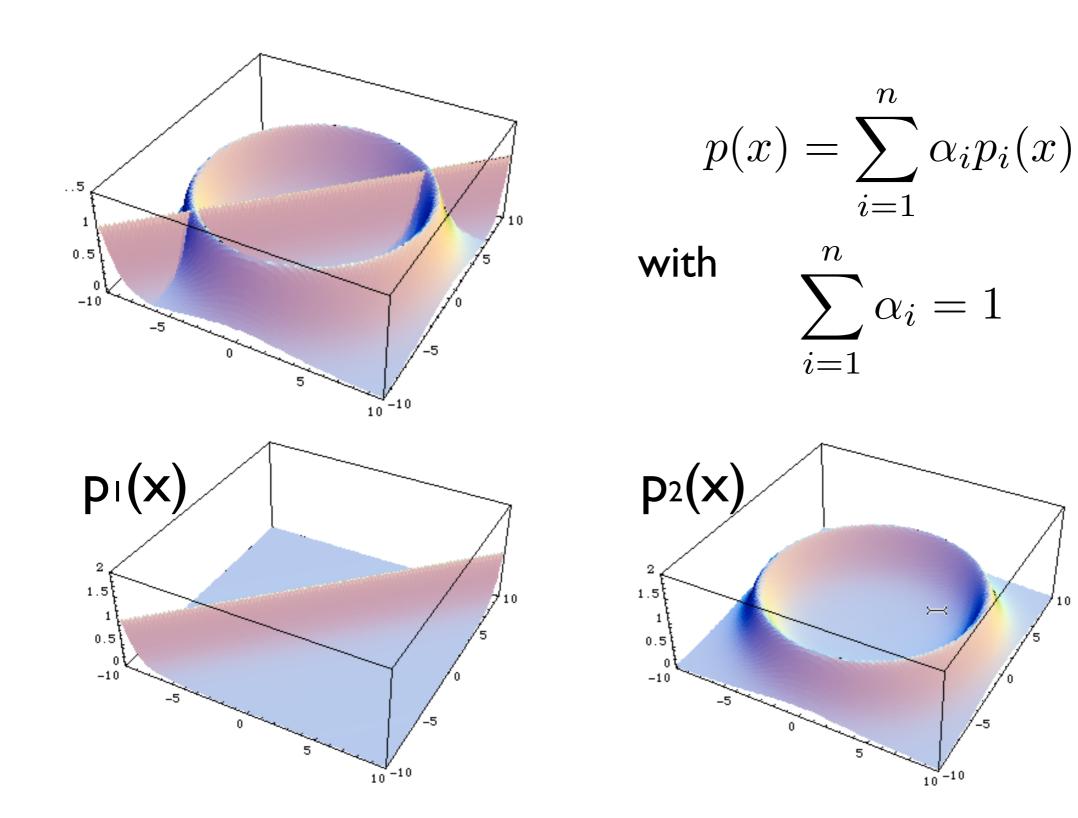
What do we do if there is no transformation that aligns all integrand peaks to the chosen axes? Vegas is bound to fail!

Solution: use different transformations = channels

$$p(x) = \sum_{i=1}^{n} \alpha_i p_i(x) \quad \text{with} \quad \sum_{i=1}^{n} \alpha_i = 1$$

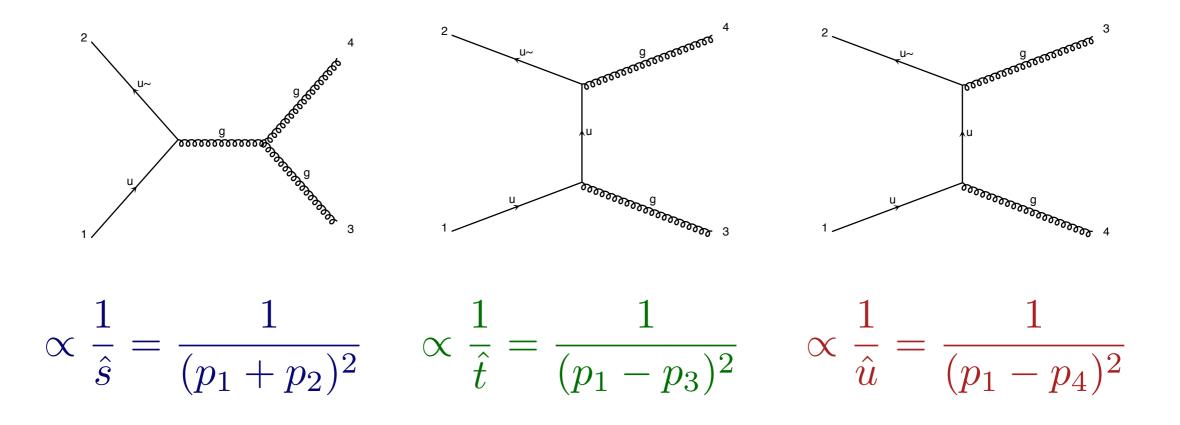
with each $p_i(x)$ taking care of one "peak" at the time

Multi-channel



10 -10

Example: QCD 2 \rightarrow 2



Three very different pole structures contributing to the same matrix element.

Single-Diagram-Enhanced technique

*Method used in MadGraph

Trick in MadEvent: Split the complexity

$$\int |M_{tot}|^2 = \int \frac{\sum_i |M_i|^2}{\sum_j |M_j|^2} |M_{tot}|^2 = \sum_i \int \frac{|M_i|^2}{\sum_j |M_j|^2} |M_{tot}|^2$$

Single-Diagram-Enhanced technique

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Trick in MadEvent: Split the complexity

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- Any single diagram is "easy" to integrate (pole $~\approx 1$ structures/suitable integration variables known from the propagators)
- Divide integration into pieces, based on diagrams
- All other peaks taken care of by denominator sum

Single-Diagram-Enhanced technique

*Method used in MadGraph

Trick in MadEvent: Split the complexity

$$\int |M_{tot}|^2 = \int \frac{\sum_i |M_i|^2}{\sum_j |M_j|^2} |M_{tot}|^2 = \sum_i \int \frac{|M_i|^2}{\sum_j |M_j|^2} |M_{tot}|^2$$

- Any single diagram is "easy" to integrate (pole structures/suitable integration variables known from the propagators)
- Divide integration into pieces, based on diagrams
- All other peaks taken care of by denominator sum

N Integral

- Errors add in quadrature so no extra cost
- "Weight" functions already calculated during $|\mathcal{M}|^2$ calculation
- Parallel in nature

$$\int |M_{tot}|^2 = \int \frac{\sum_i |M_i|^2}{\sum_j |M_j|^2} |M_{tot}|^2 = \sum_i \int \frac{|M_i|^2}{\sum_j |M_j|^2} |M_{tot}|^2$$

P1 qq wpwm

s= 725.73 ± 2.07 (pb)

<u>Graph</u>	Cross-Section ↓	<u>Error</u>	<u>Events (K)</u>	<u>Unwgt</u>	<u>Luminosity</u>
G2.2	<u>377.6</u>	1.67	142.285	7941.0	21
G3	<u>239</u>	1.16	220.04	10856.0	45.5
G1	<u>109.1</u>	0.378	70.88	3793.0	34.8

P1 gg wpwm

s= 20.714 ± 0.332 (pb)

<u>Graph</u>	Cross-Section ↓	<u>Error</u>	Events (K)	<u>Unwgt</u>	<u>Luminosity</u>
G1.2	<u>20.71</u>	0.332	7.01	373.0	18

term of the above sum.

each term might not be gauge invariant

Question time



Allez sur wooclap.com

Entrez le code d'événement dans le bandeau supérieur

Code d'événement MADGRAPH

Activer les réponses par SMS

To Remember

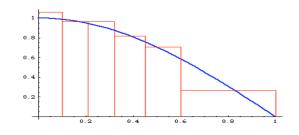
- Phase-Space integration is difficult
- We need to know the function
 - Be careful with cuts
- MadGraph split the integral in different contribution linked to the Feynman Diagram

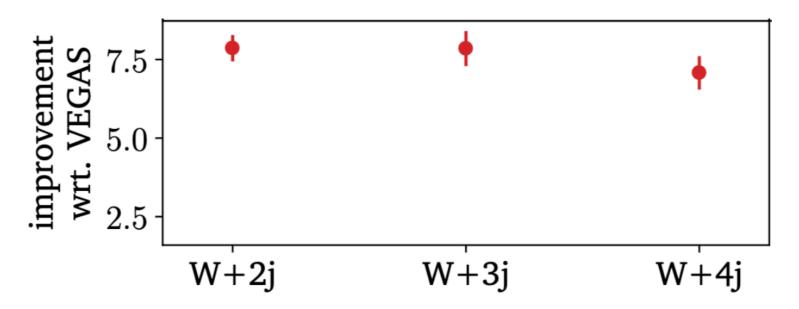
Those are not the contribution of a given diagram

Can we do Better?

- Importance sampling/VEGAS is learning a function
 - HOT TOPIC: Machine Learning
 - Lot of work in progress

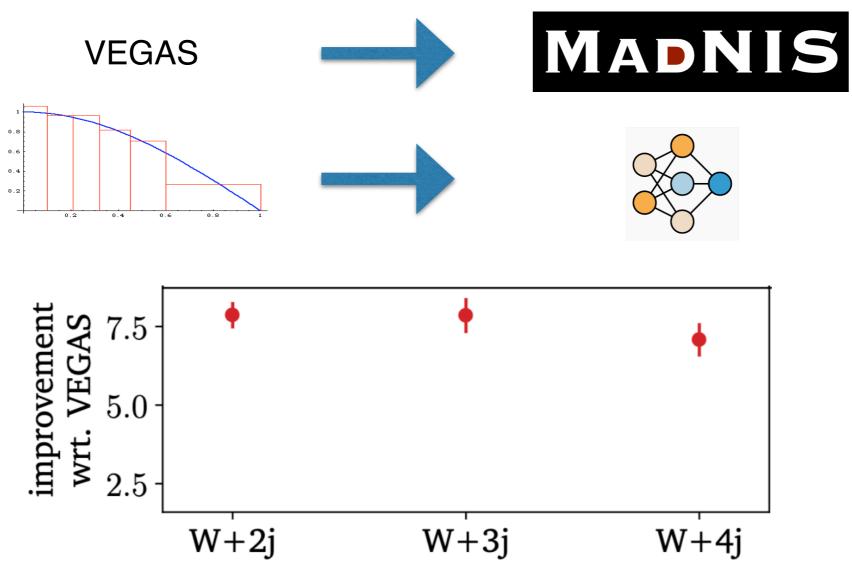
VEGAS





Can we do Better?

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 - Lot of work in progress

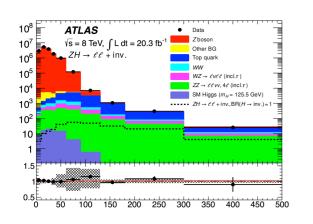


Event Generation

What is the goal?

Cross-section

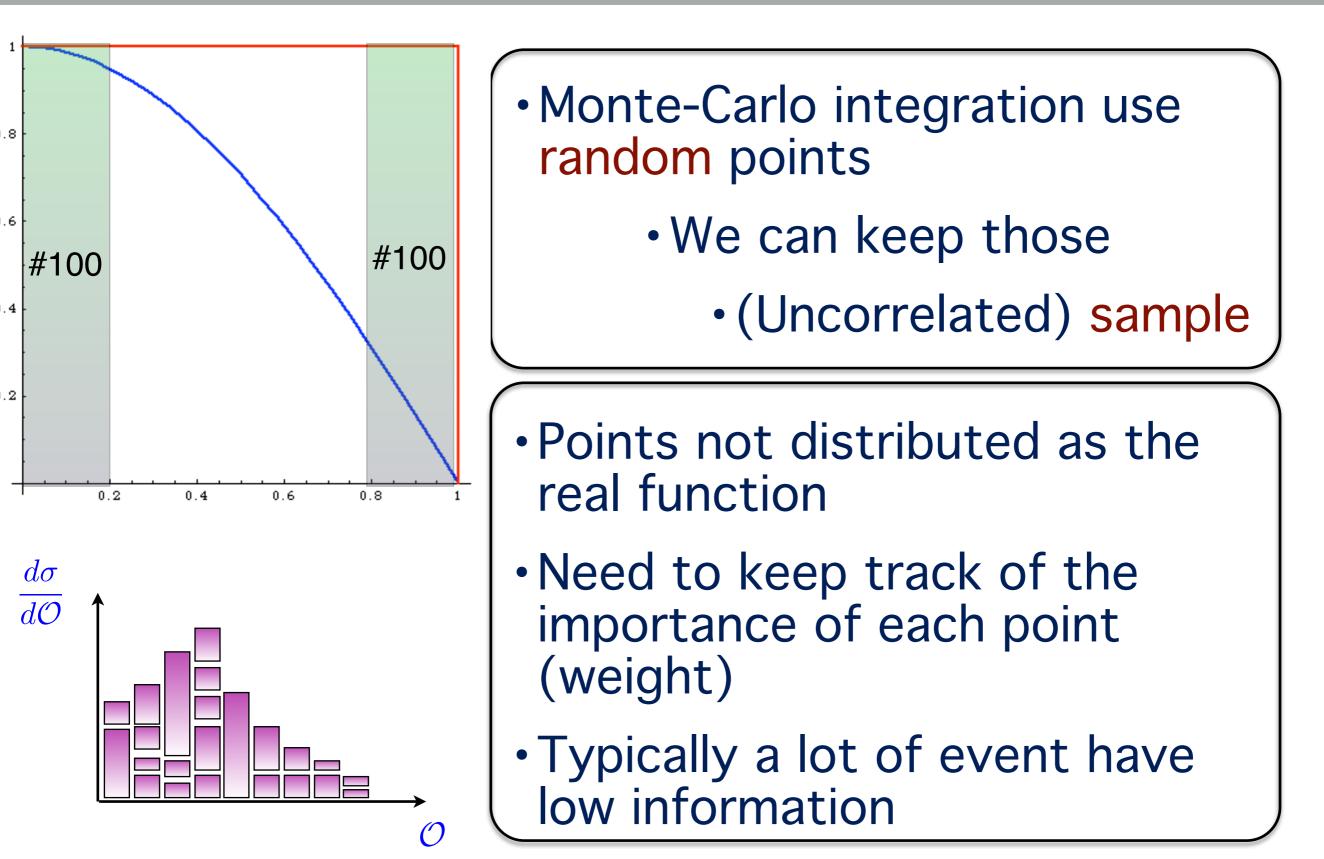
But large theoretical uncertainty

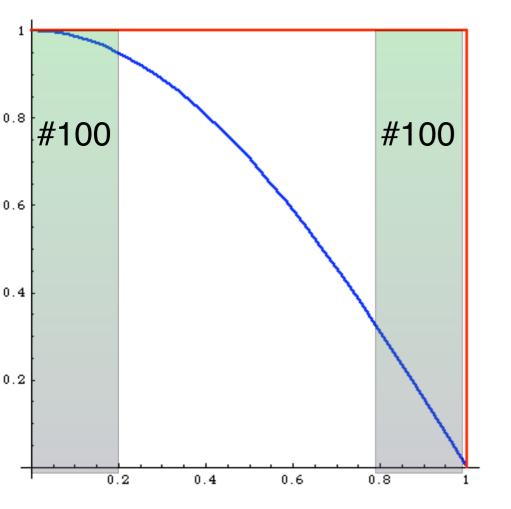


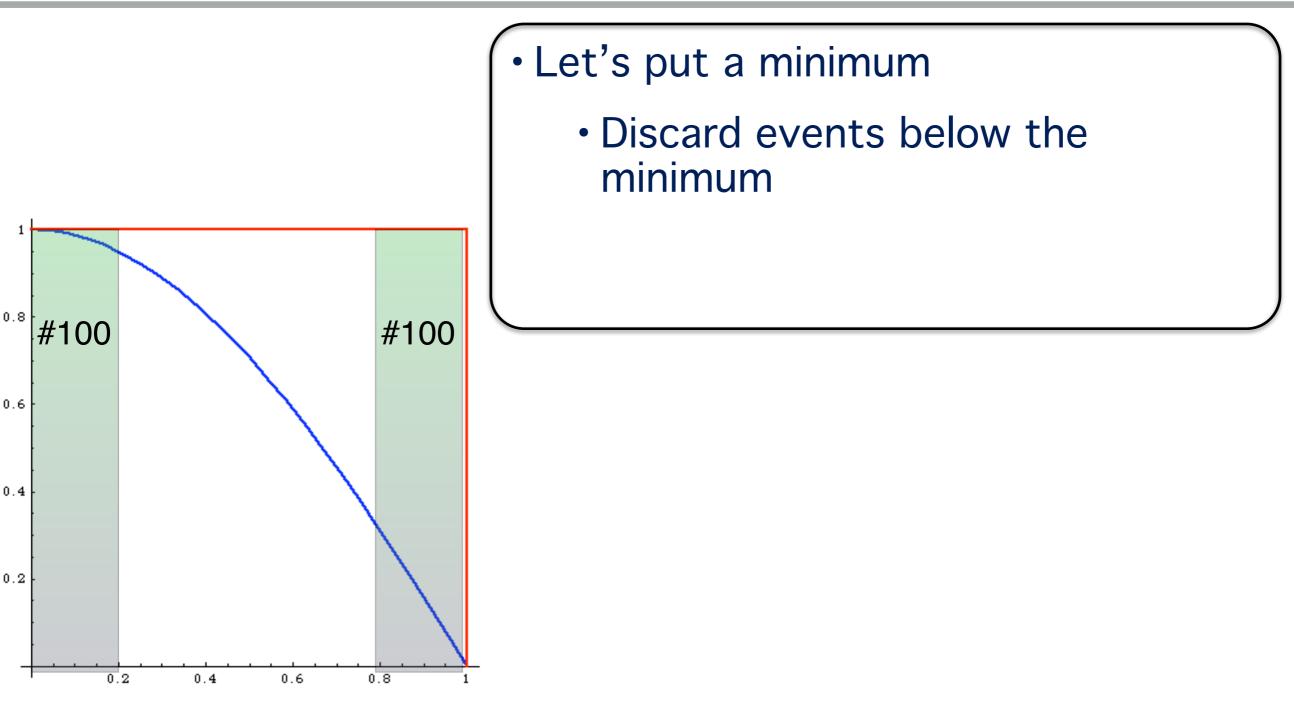
Differential Cross-Section

- Provided as sample of events
- Sample size is problematic
 - Those events will need to have full detector simulation

How to get sample?

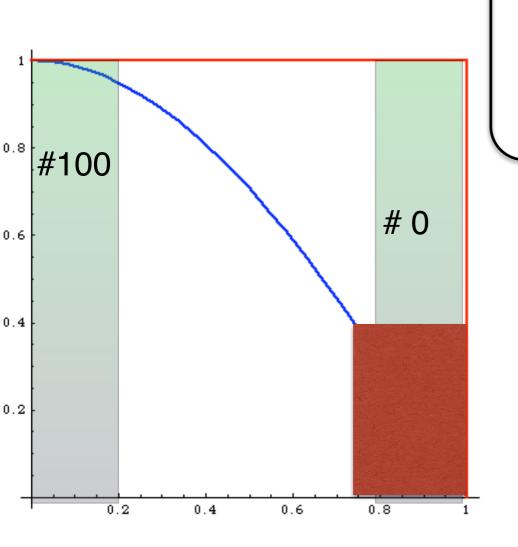






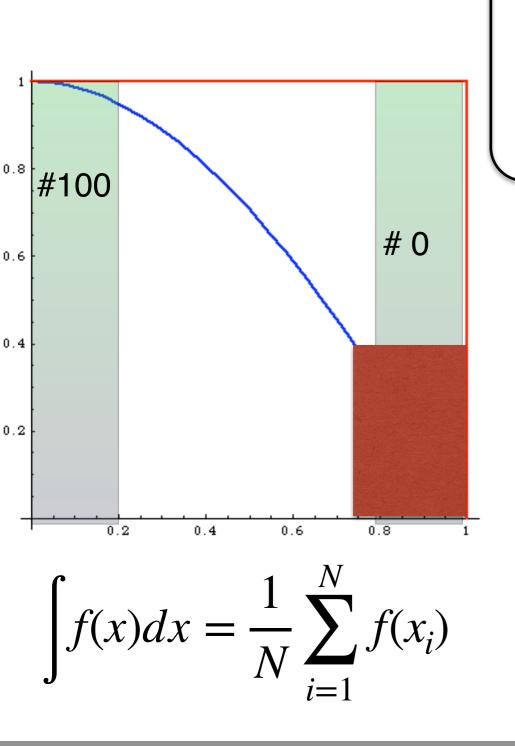


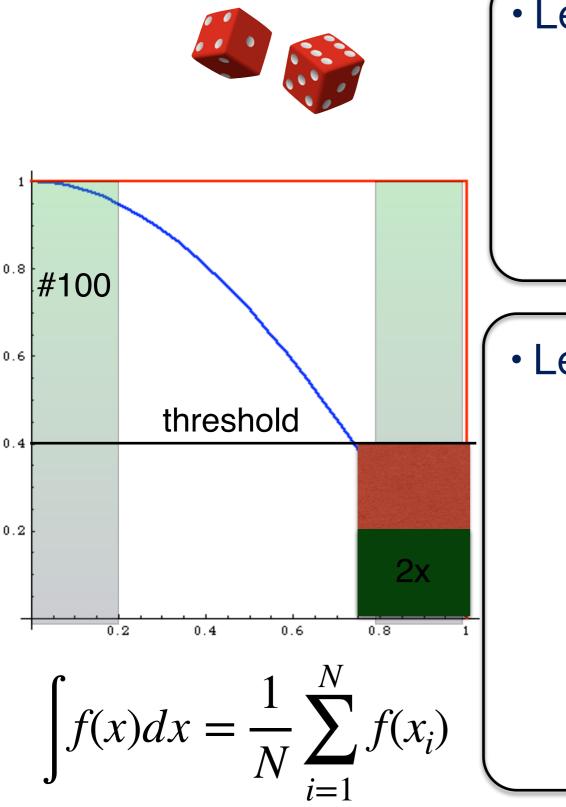
 Discard events below the minimum



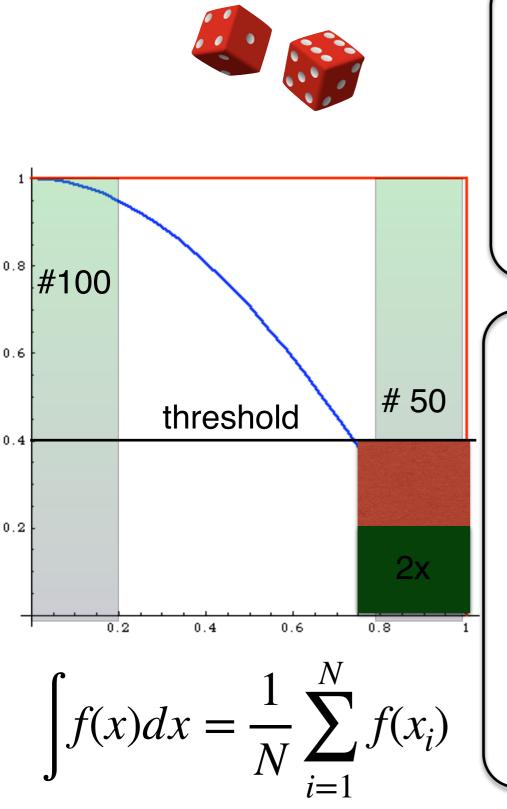


- Discard events below the minimum
- NO! We loose cross-section/ bias ourself





- Discard events below the minimum
- NO! We loose cross-section/ bias ourself
- Let's put a minimum
 - But keep 50% of the events below

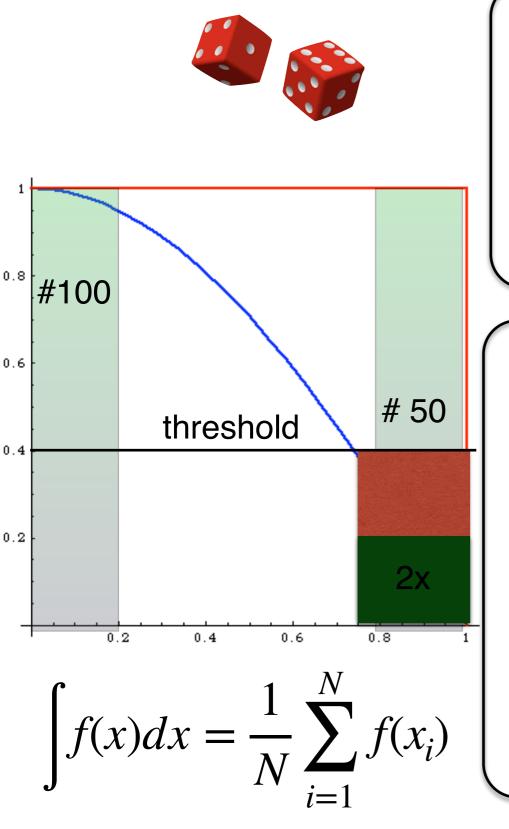


• Let's put a minimum

- Discard events below the minimum
- NO! We loose cross-section/ bias ourself

Let's put a minimum

But keep 50% of the events below

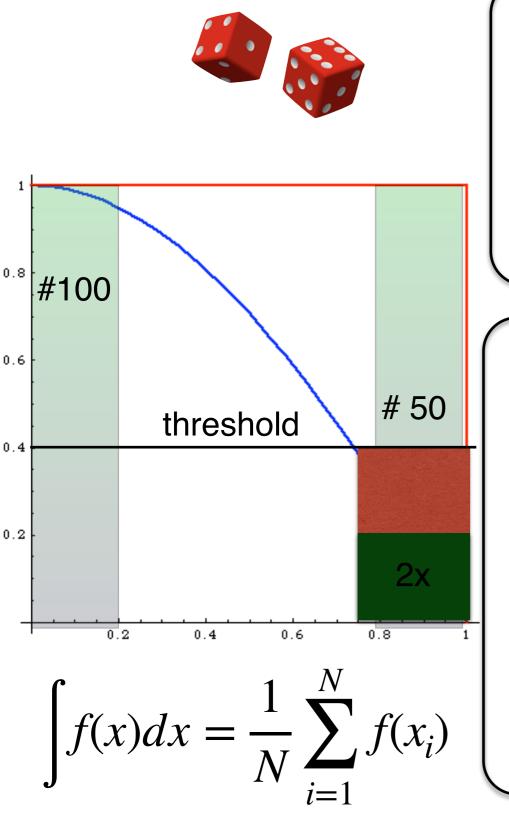


Let's put a minimum

- Discard events below the minimum
- NO! We loose cross-section/ bias ourself

• Let's put a minimum

- But keep 50% of the events below
- Multiply the weight of each event by 2 (preserve cross-section)



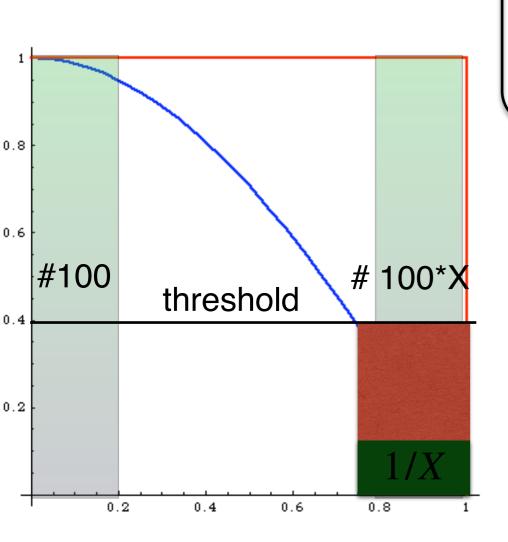
Let's put a minimum

- Discard events below the minimum
- NO! We loose cross-section/ bias ourself

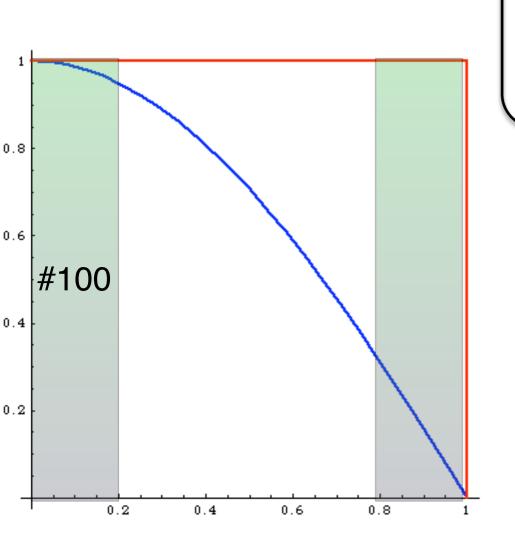
Let's put a minimum

- But keep 50% of the events below
- Multiply the weight of each event by 2 (preserve cross-section)
- We loose information
- But we gain in file size

- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)

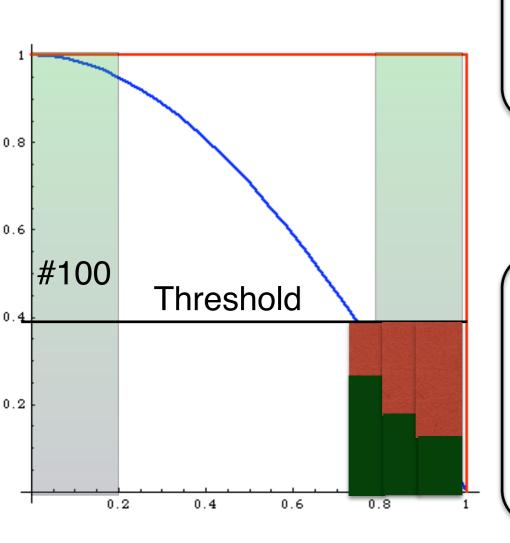


- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)

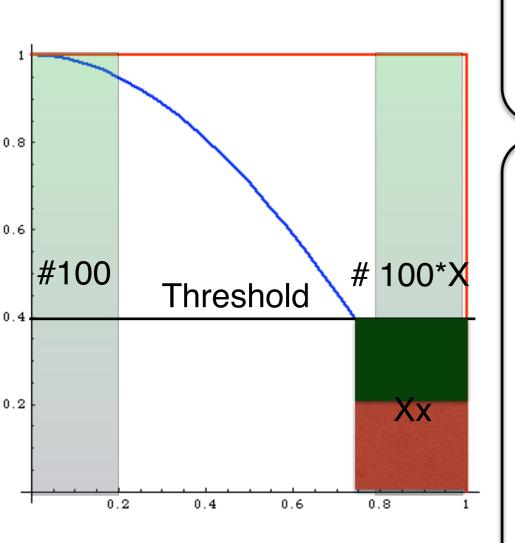


- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)

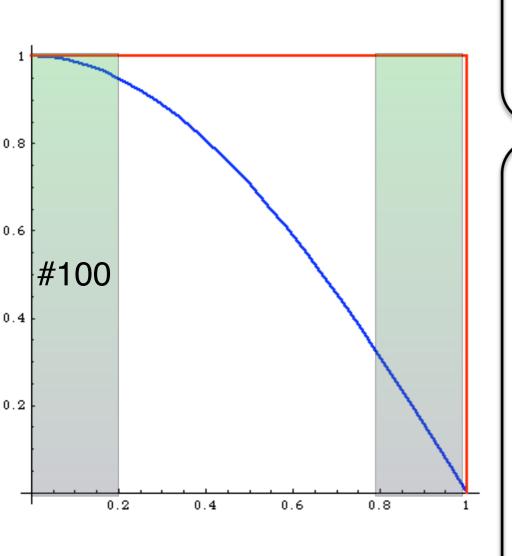
- Let's improve
 - We could reject more event (change X) where the function is small



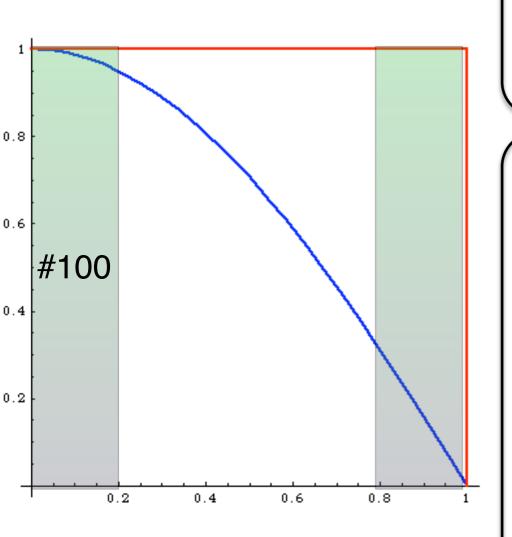
- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)



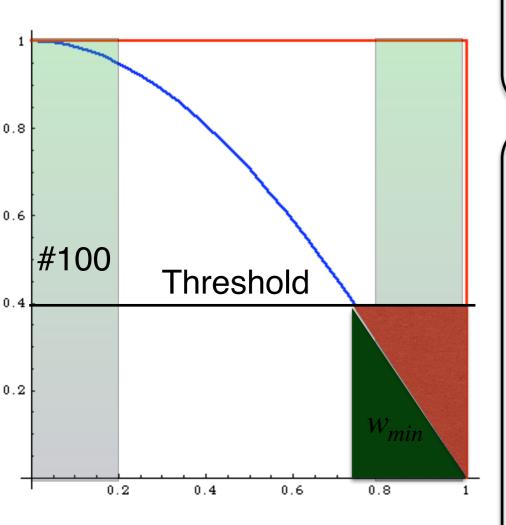
- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)



- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)
- Let's improve
 - Let's make the threshold proportional to the weight



- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)
- Let's improve
 - Let's make the threshold proportional to the weight



Let's put a threshold

- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)
- Let's improve
 - Let's make the threshold proportional to the weight
 - . Keep each event with probability

0.2

0.8

0.6

0.4

0.2

#100

Threshold

0.4

0.6

0.8

100w %

*W*_{thres}

Let's put a threshold



 Multiply the weight of each event by 1/X (preserve cross-section)

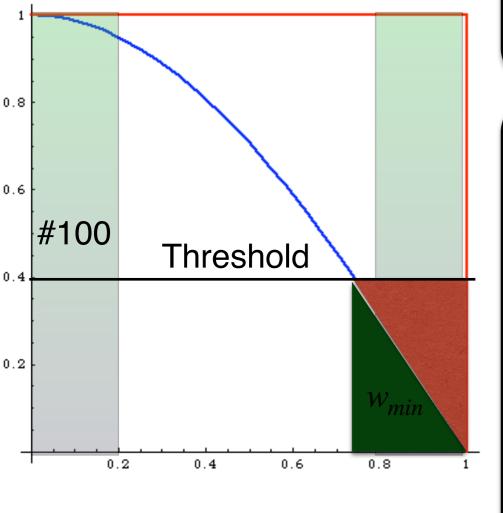
Let's improve

- Let's make the threshold proportional to the weight
- 100w % . Keep each event with probability
- . If kept multiply his weight by



W

*W*_{thres}



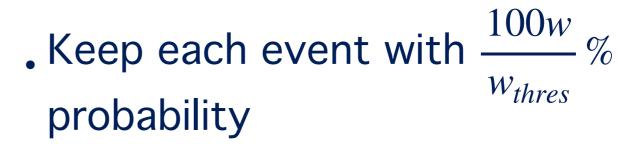
Let's put a threshold



 Multiply the weight of each event by 1/X (preserve cross-section)

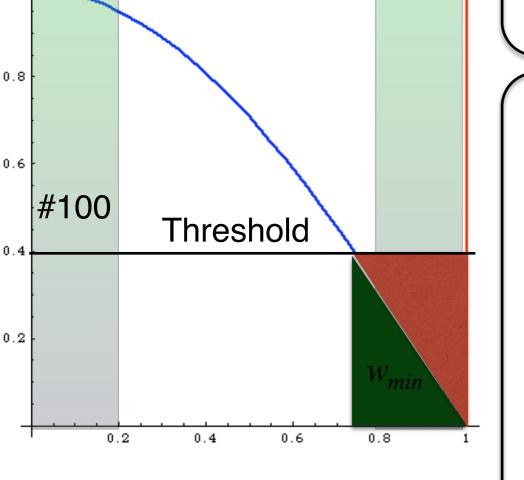
Let's improve

• Let's make the threshold proportional to the weight



. If kept multiply his weight by

• So the new weight is *w*_{thres}



W_{thres}

W

Let's put a threshold

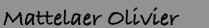
- But keep X*100% of the events below
- Multiply the weight of each event by 1/X (preserve cross-section)

Let's improve

#8

0.8

- Let's make the threshold proportional to the weight
- . Keep each event with $\frac{100w}{w_{thres}}$ % probability
- . If kept multiply his weight by
- So the new weight is *w*_{thres}



0.2

0.8

0.6

0.4

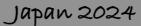
0.2

#100

Threshold

0.4

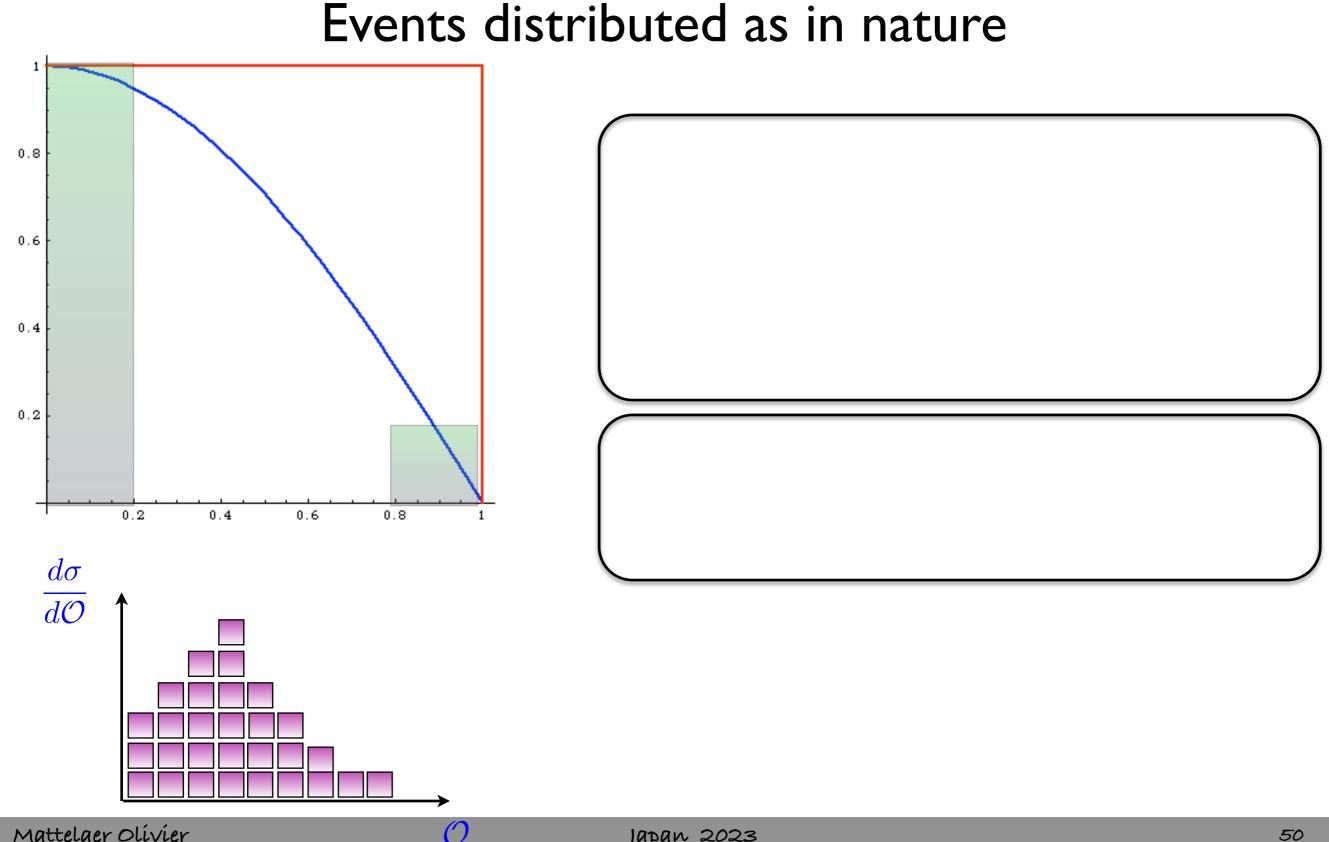
0.6



W_{thres}

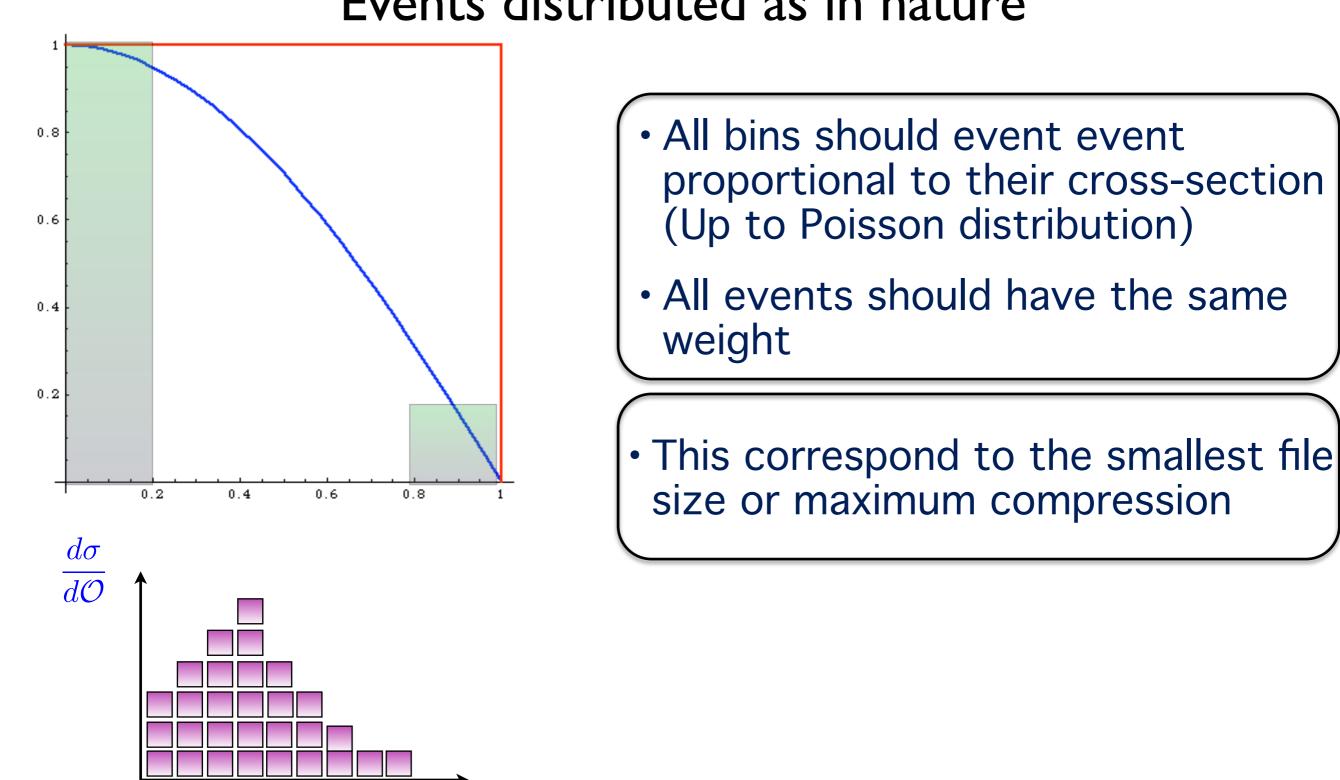
W

Unweighted events



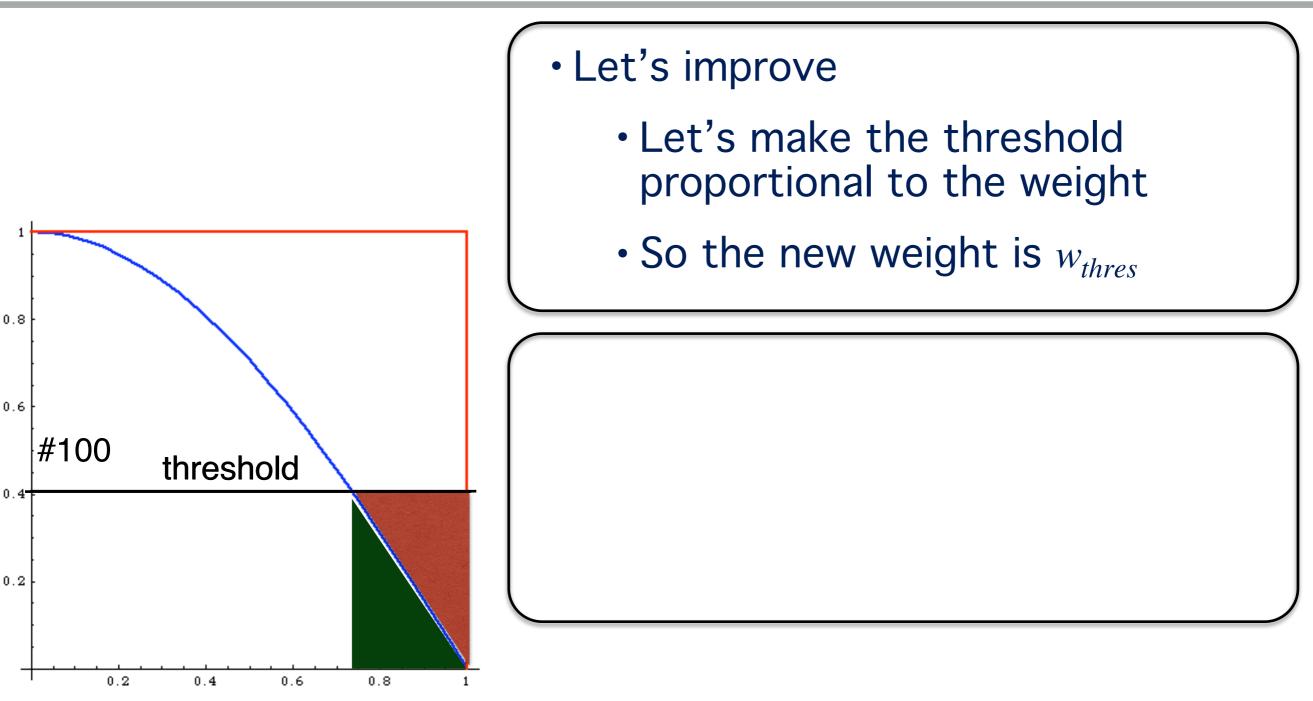
Mattelaer Olivier

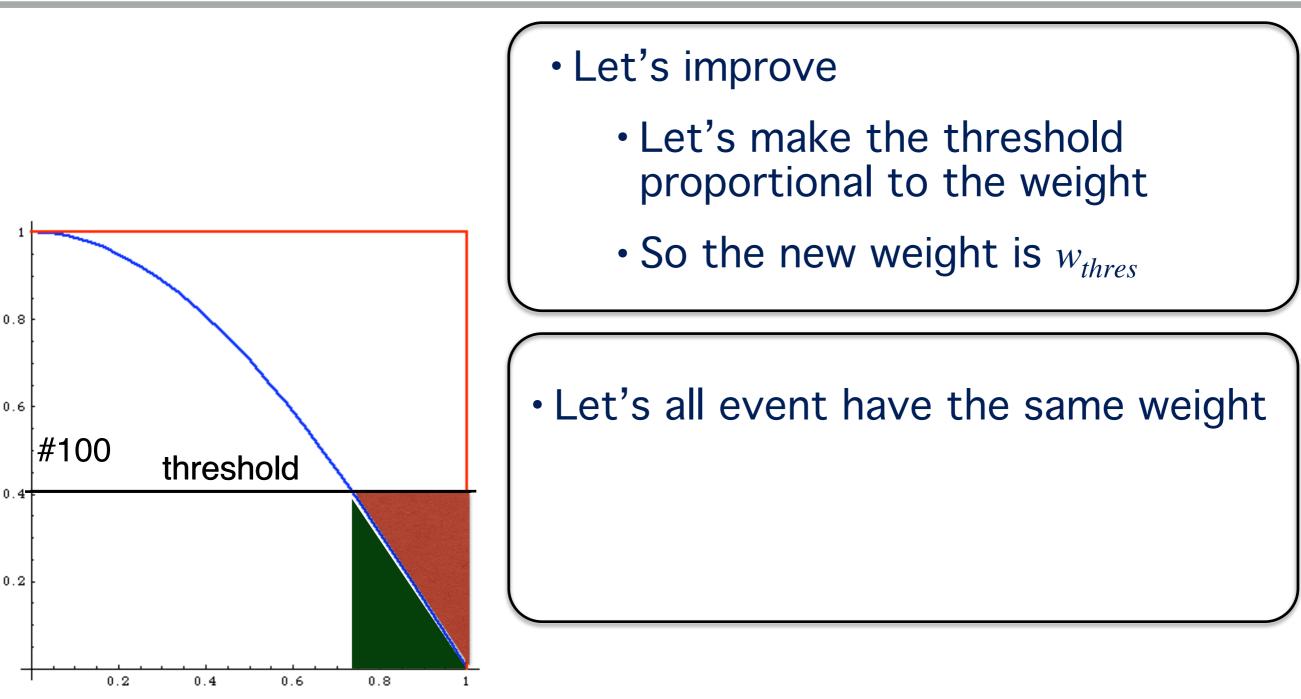
Unweighted events

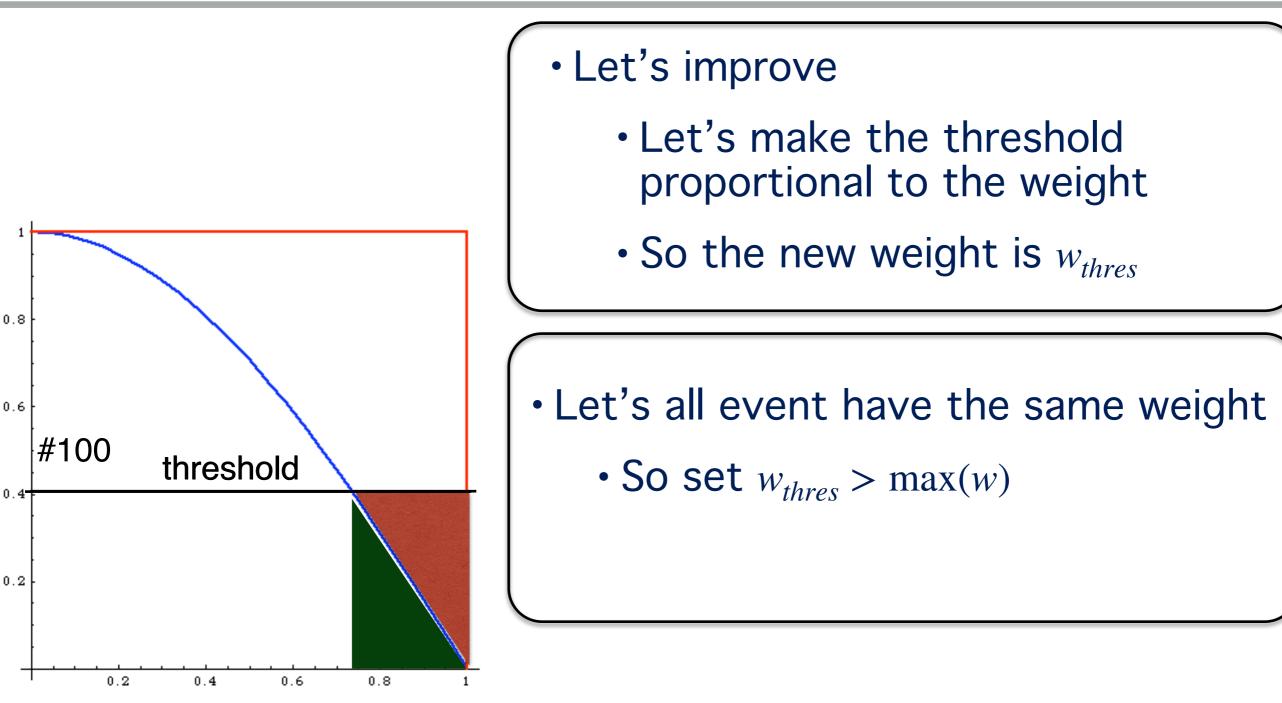


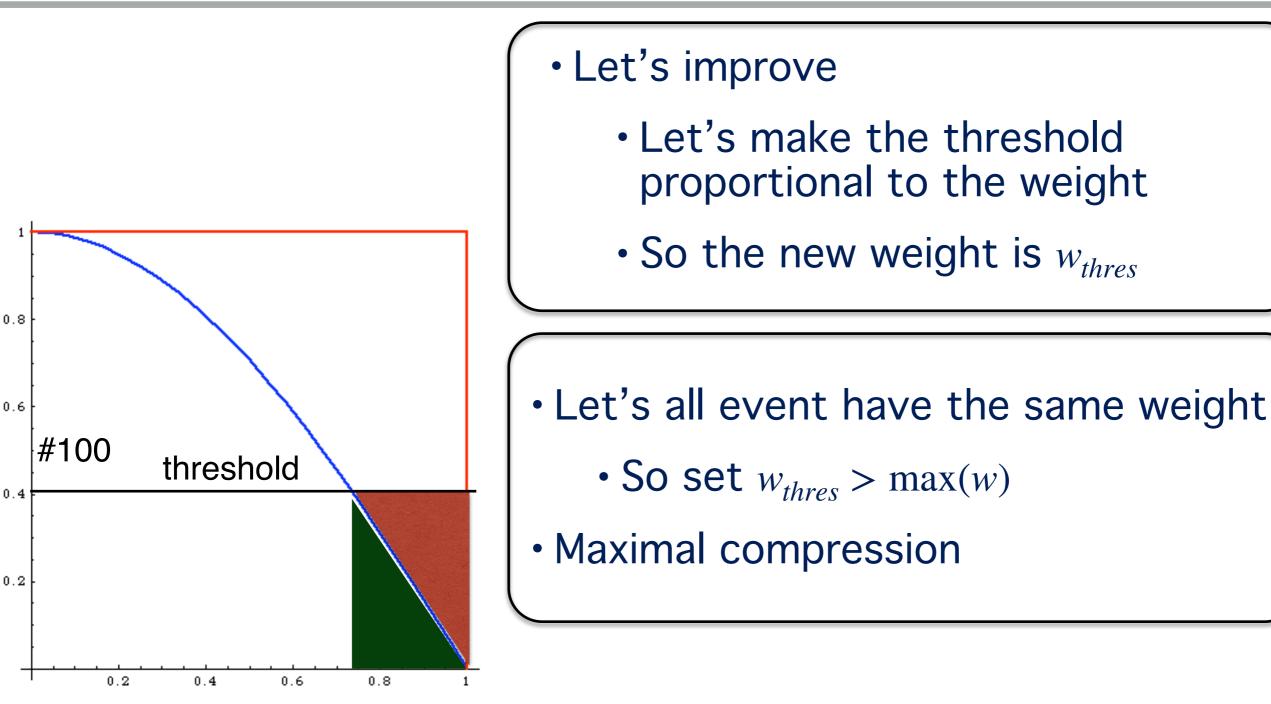
Events distributed as in nature

(')





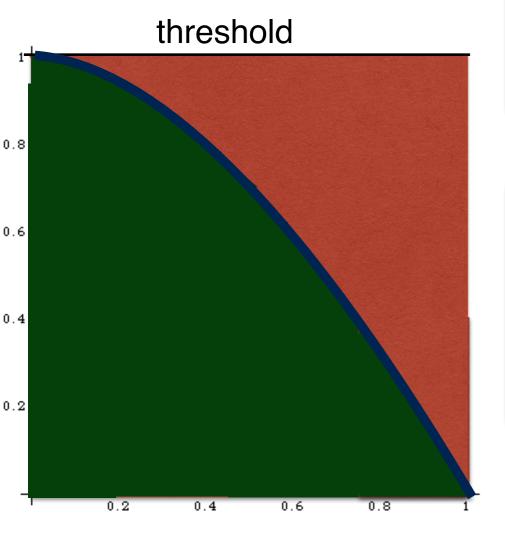


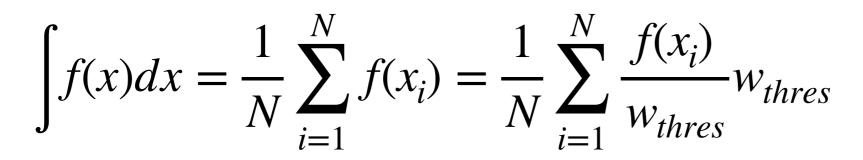


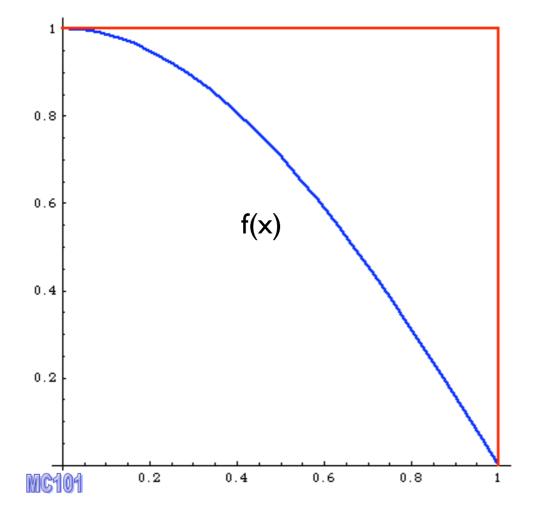


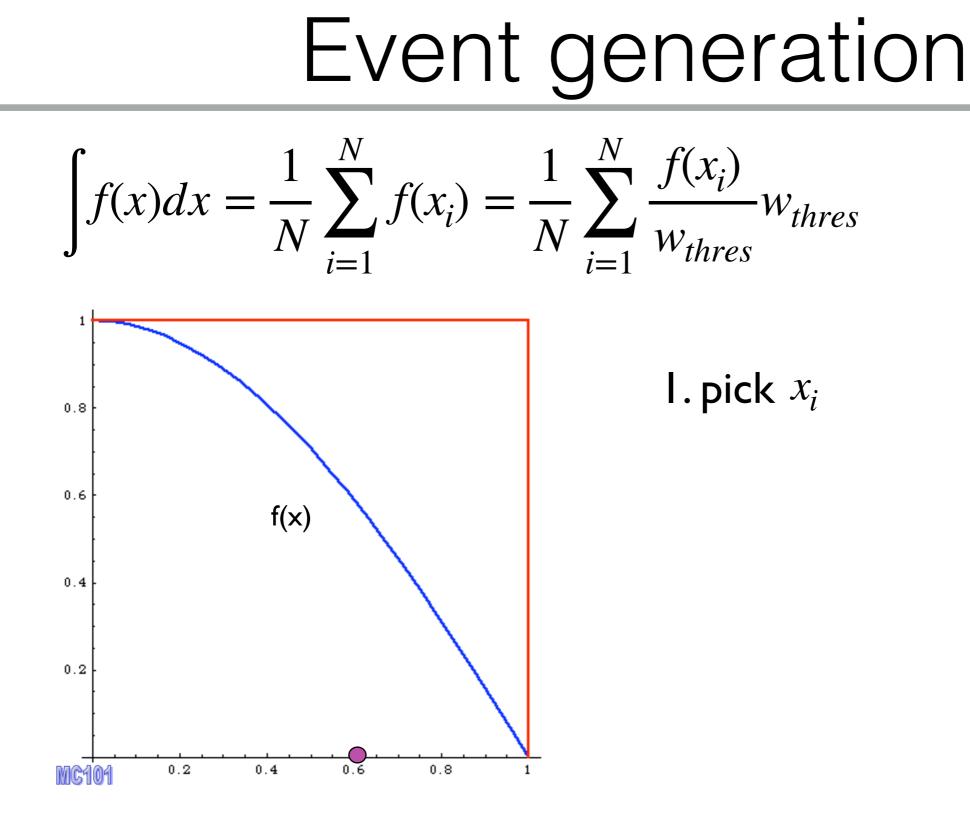
- Let's make the threshold proportional to the weight
- So the new weight is w_{thres}

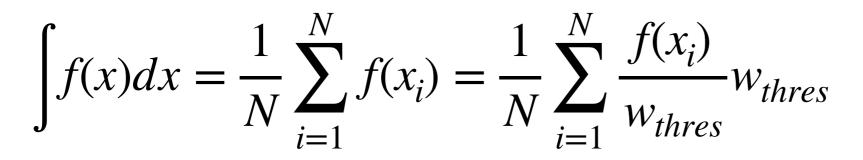
- Let's all event have the same weight
 - So set $w_{thres} > \max(w)$
- Maximal compression

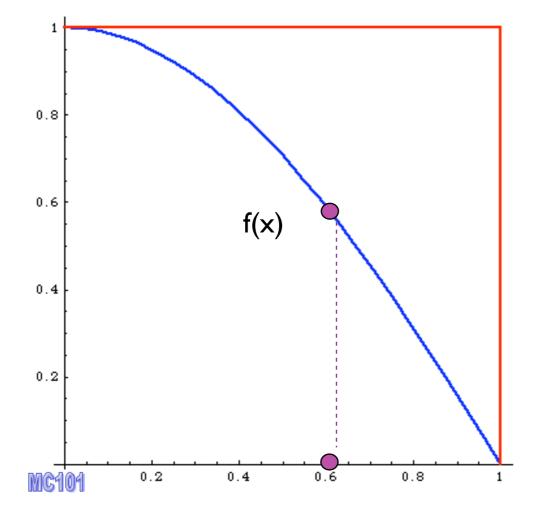








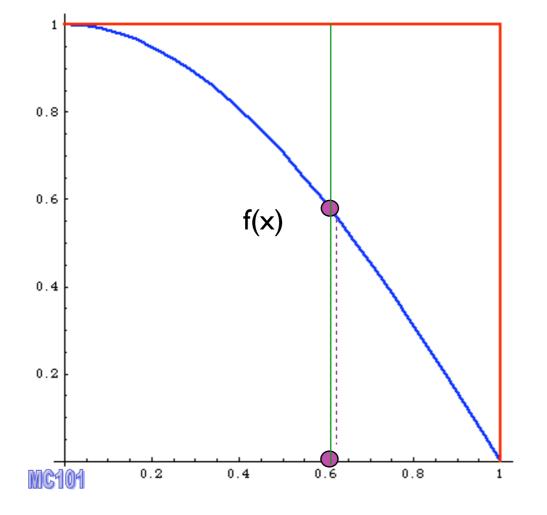




I. pick x_i

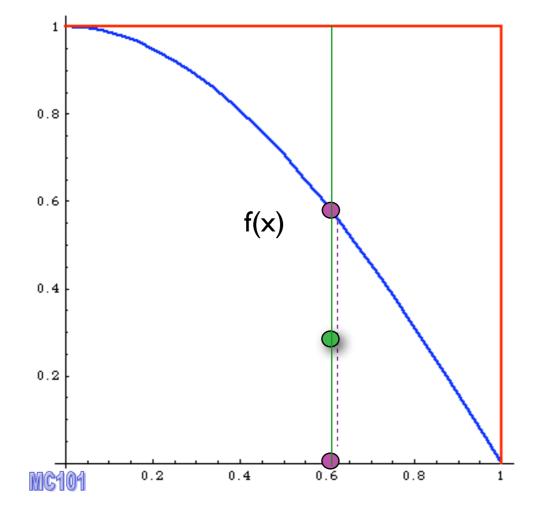
2. calculate $f(x_i)$

$$\int f(x)dx = \frac{1}{N} \sum_{i=1}^{N} f(x_i) = \frac{1}{N} \sum_{i=1}^{N} \frac{f(x_i)}{w_{thres}} w_{thres}$$



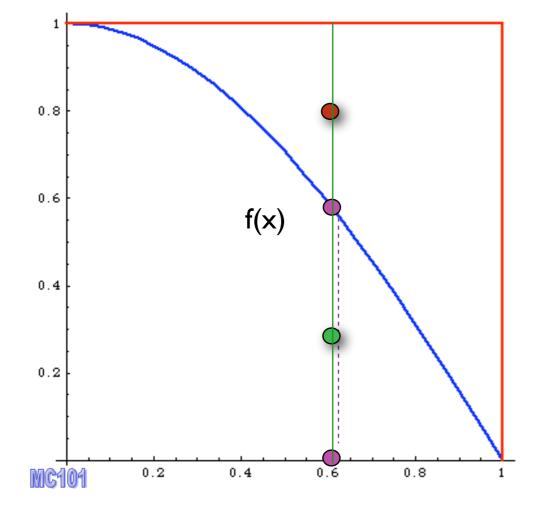
- I. pick x_i
- 2. calculate $f(x_i)$
- **3.** pick $y \in [0, max(f)]$

$$\int f(x)dx = \frac{1}{N} \sum_{i=1}^{N} f(x_i) = \frac{1}{N} \sum_{i=1}^{N} \frac{f(x_i)}{w_{thres}} w_{thres}$$

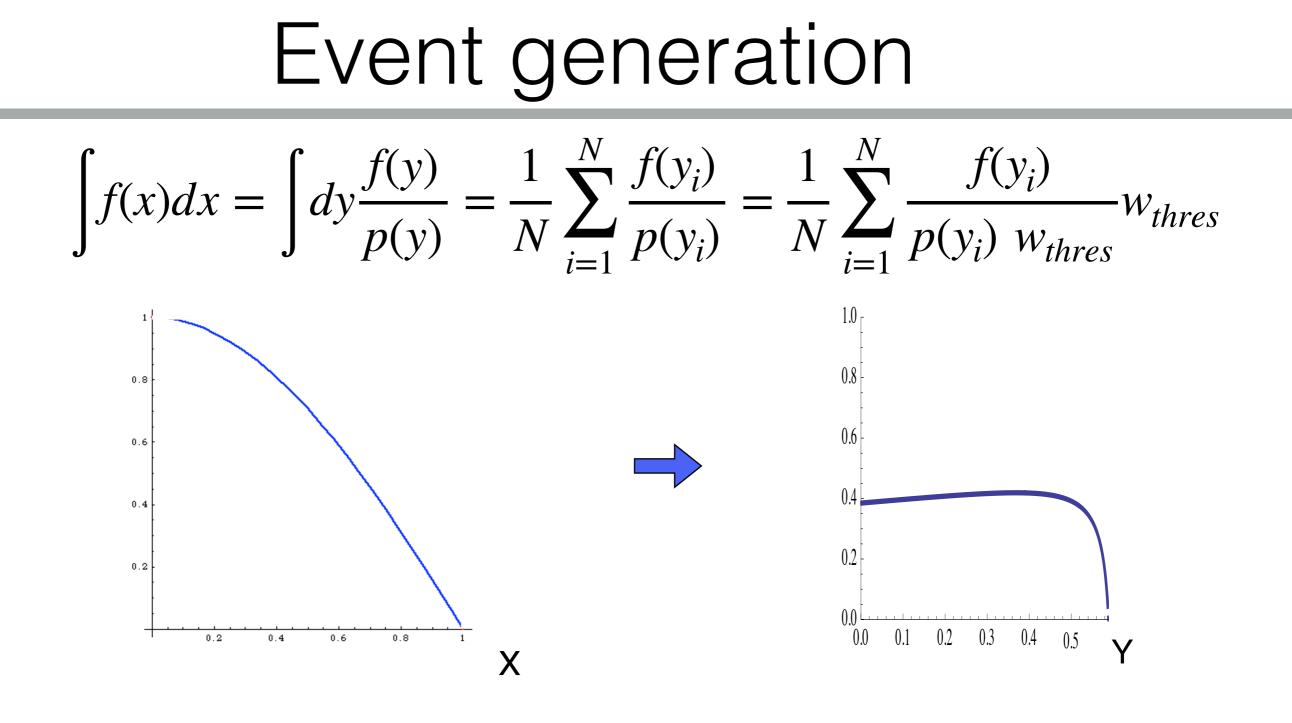


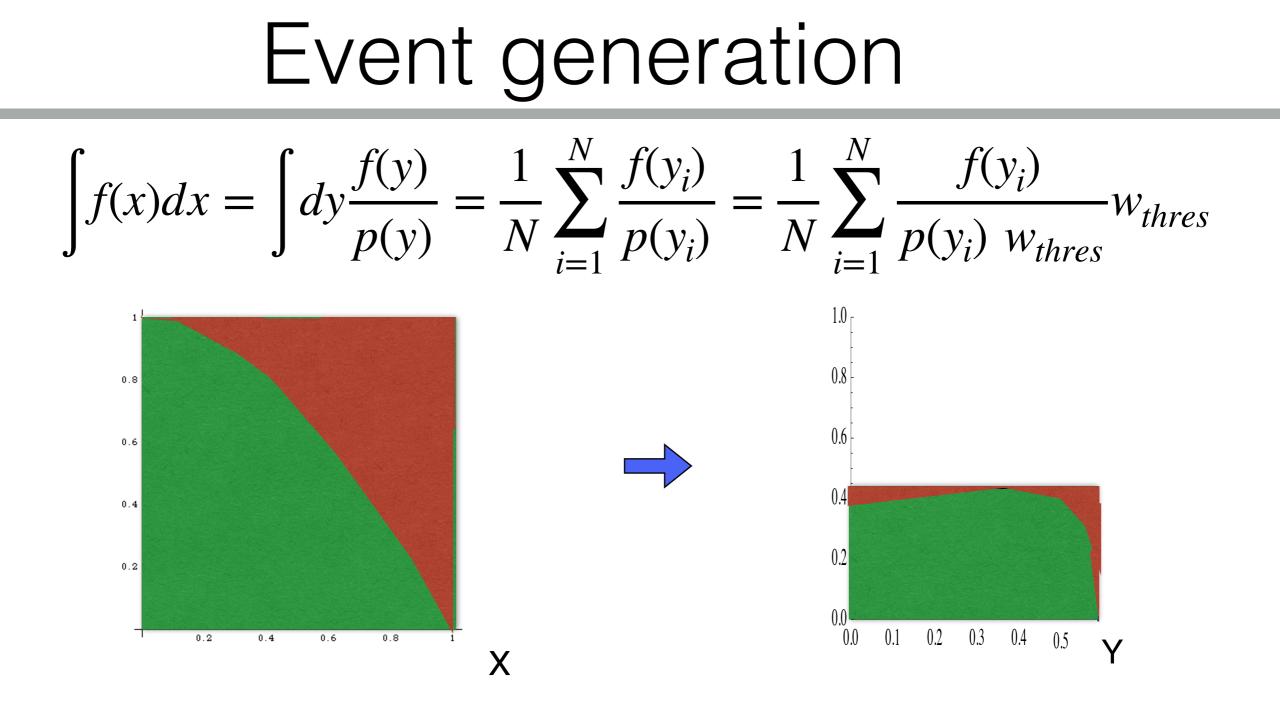
- I. pick x_i
- 2. calculate $f(x_i)$
- **3.** pick $y \in [0, max(f)]$
- 4. Compare: if $y < f(x_i)$ accept event,

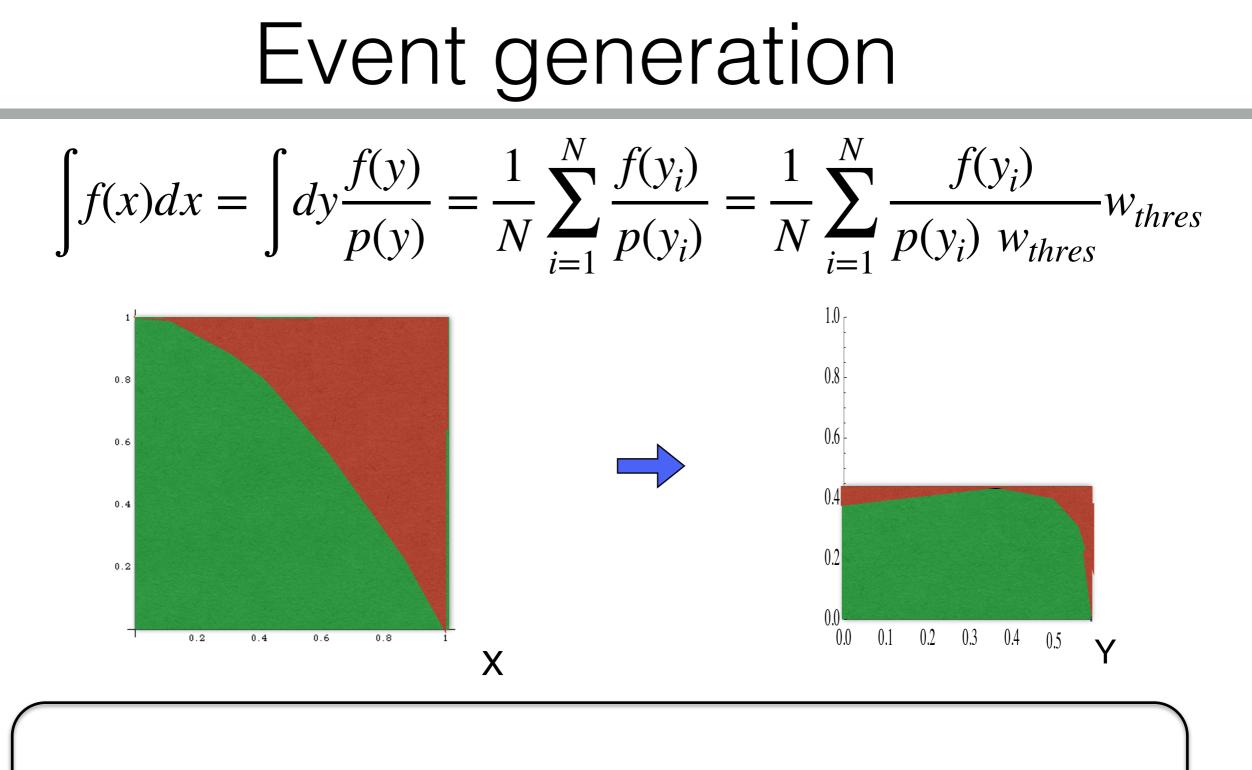
$$\int f(x)dx = \frac{1}{N} \sum_{i=1}^{N} f(x_i) = \frac{1}{N} \sum_{i=1}^{N} \frac{f(x_i)}{w_{thres}} w_{thres}$$



- I. pick x_i
- 2. calculate $f(x_i)$
- **3. pick** $y \in [0, max(f)]$
- 4. Compare: if $y < f(x_i)$ accept event,
 - else reject it.







• Having smaller variance (flatter function) also allows to have $\frac{w}{w_{thres}}$ or $\frac{w}{max(w)}$ closer to one and therefore better unweighting efficiency (i.e. faster code)