

Exploring the Matrix Element Method and its Application to $t\bar{t}$ Events

Alec Josaitis, Undergraduate Researcher

Tancredi Carli, Research Physicist

The ATLAS Experiment, CERN, Meyrin, Switzerland

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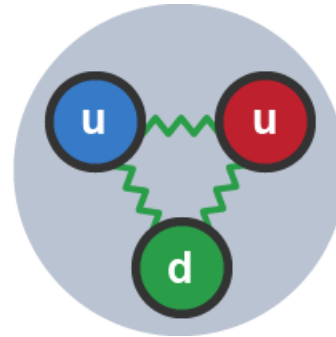


The Top Quark and its Uniqueness

- Heaviest Elementary Particle

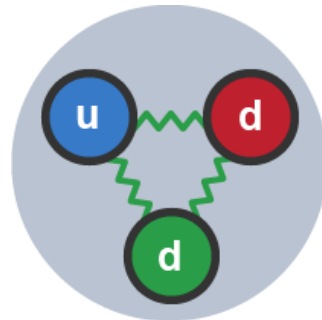
$172.99 \pm 0.48 \text{ (stat)} \pm 0.78 \text{ (syst)} \text{ GeV}/c^2$ (ATLAS 7 TeV data)

“66 Millionths... of a billionth... of a billionth... of a pound”



= 79 Protons
+
118 Neutrons

= 183.43 GeV/c^2
(HyperPhysics)

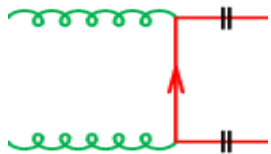


The Top Quark and its Uniqueness

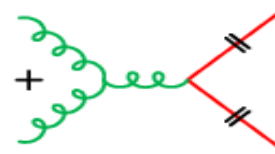
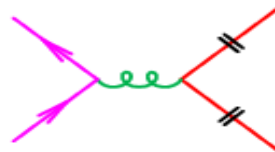
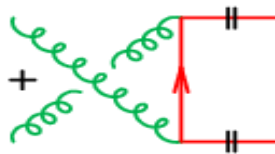
- Heaviest Elementary Particle

172.99 \pm 0.48 (stat) \pm 0.78 (syst) GeV (ATLAS 7 TeV data)

- Natural laboratory for studying Higgs interaction with matter.
- High Mass \rightarrow Short lifetime: 5×10^{-25} s.



$q\bar{q} \rightarrow t\bar{t}$

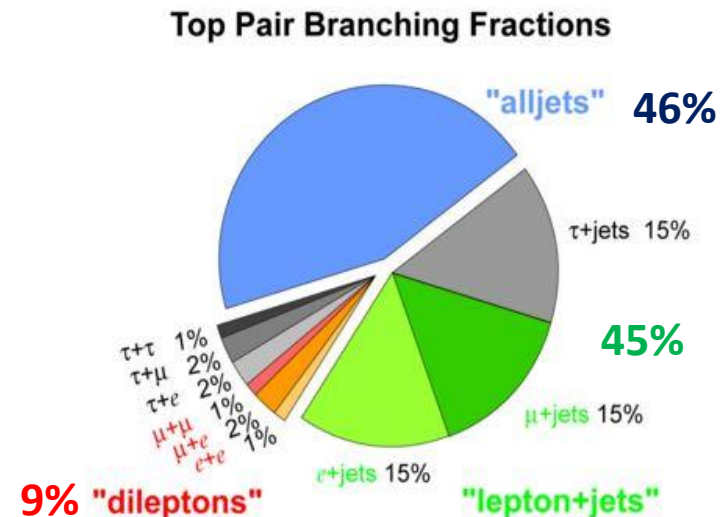
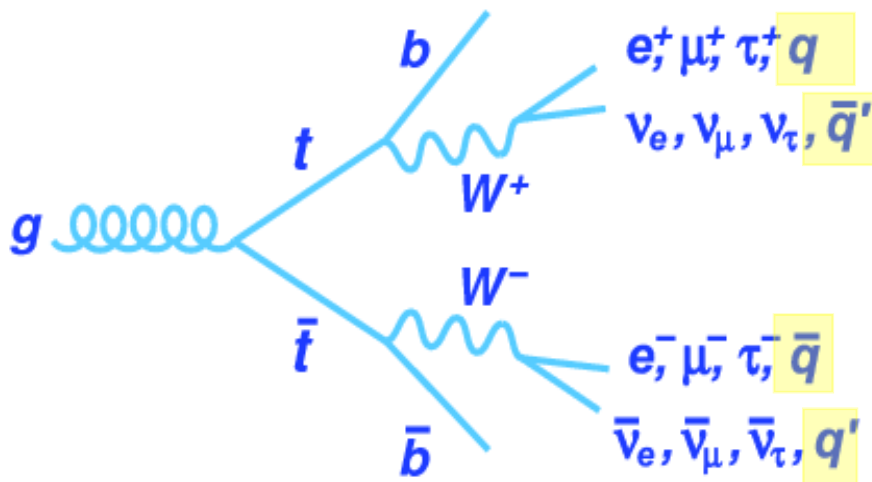


$gg \rightarrow t\bar{t}$

Hard Scattering
Production Processes
from proton-proton
collisions.

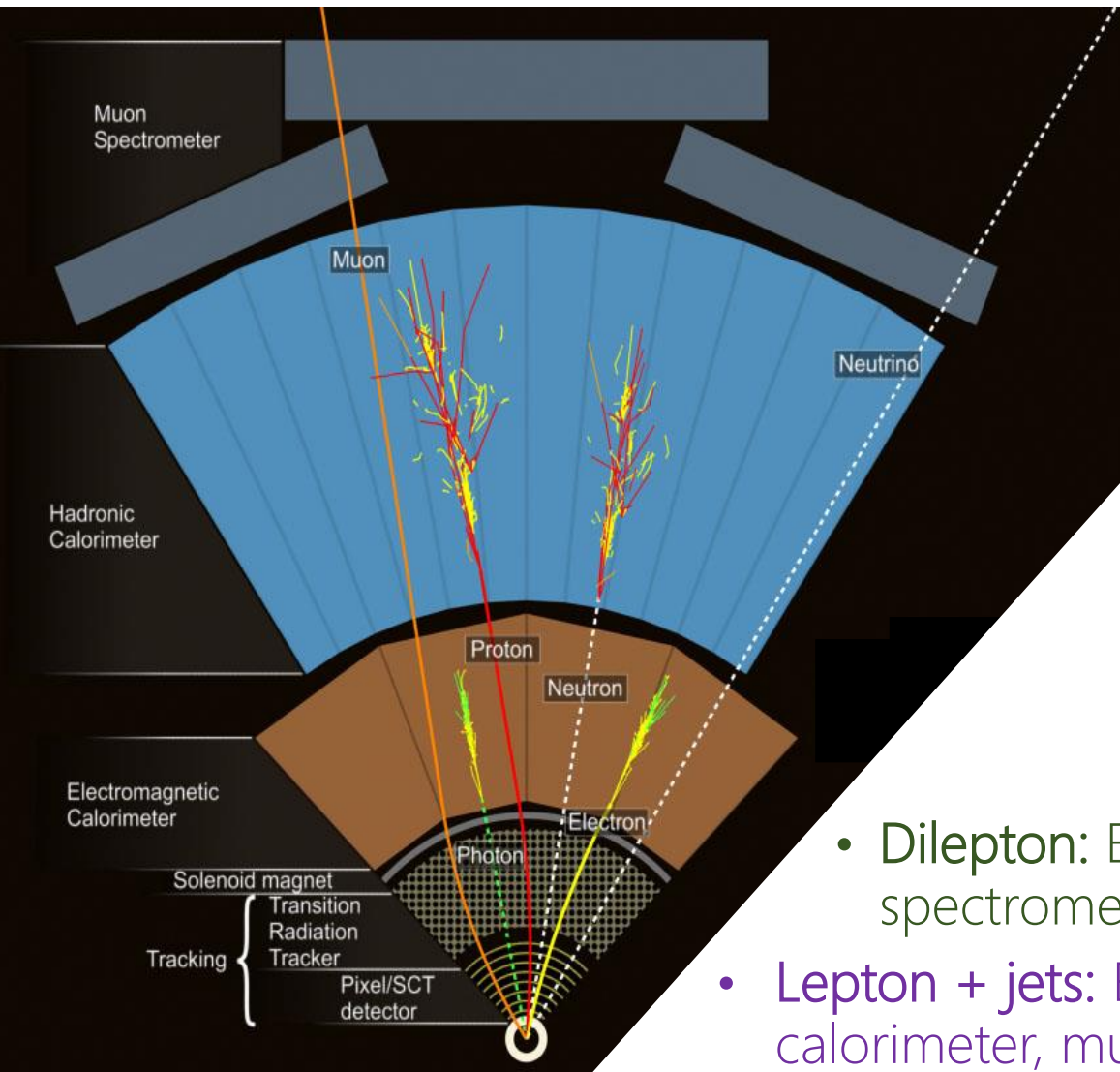
Decay Processes (Leading Order)

- Top quarks can decay in different ways, each with its own likelihood
- Goal: Reconstruct kinematic properties of the top quark using the decay products
- Three categories: “Dilepton” vs. “Lepton + Jets” vs. “Alljets”



Courtesy of D0 Collaboration

The ATLAS Detector- Observables



- 4 vectors of all leading order decay products can be detected, except neutrinos.

$$H_x = p_{v_x} + p_{\bar{v}_x}$$

$$H_y = p_{v_y} + p_{\bar{v}_y}$$

$$E_v^2 = p_{v_x}^2 + p_{v_y}^2 + p_{v_z}^2 \rightarrow p_v^2 = 0$$

$$E_{\bar{v}}^2 = p_{\bar{v}_x}^2 + p_{\bar{v}_y}^2 + p_{\bar{v}_z}^2 \rightarrow p_{\bar{v}}^2 = 0$$

$$m_{W^+}^2 = (p_{l^+} + p_v)^2$$

$$m_{W^-}^2 = (p_{l^-} + p_{\bar{v}})^2$$

$$m_l^2 = (p_{l^+} + p_v + p_b)^2$$

$$m_{\bar{l}}^2 = (p_{l^-} + p_{\bar{v}} + p_{\bar{b}})^2.$$

- Dilepton: EM calorimeter and muon spectrometer.
- Lepton + jets: EM calorimeter, hadronic calorimeter, muon spectrometer.

ReadFromSherpa – A Simple Example

- Use algorithms and operational definitions to reconstruct a $t\bar{t}$ event.
- Determine $P(\text{event})$ using simple, 2D profile histogram as a “look-up” table.

Loop over all events

- Use observable theory (b and lepton selection) to identify all possible “configurations” (combinations of three particles, a top candidate)
- Determine if Δ variable algorithm chose the correct configuration
- Create and fill maps of configuration properties (true and algorithm)

Normalize histograms ($\Sigma \text{weights} / N_{\text{entries}}$) = $\langle \text{weight} \rangle$

Loop over all events

Loop over all configurations

- Calculate probability $P(\text{variable1}, \dots, \text{variableN})$ using $\langle \text{weight} \rangle$
- Select configuration with highest probability

Determine performance of Δ variable and probability algorithms

ReadFromSherpa

Current performance (10,000 dilepton entries)
 Δ relative mass: 97.48% Accurate
 $P(x_1, \Delta \text{ rel.mass})$: 98.30% Accurate

Previously

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Loop over all events

Loop over all configurations

- Calculate probability $P(\text{variable}_1, \dots, \text{variable}_N)$ using $\langle \text{weight} \rangle$
- Select configuration with highest probability

Determine performance of Δ variable and probability algorithms

New Goal: Calculate $P(\text{event})$ using n-dimensional data structure.

A Computationally Expensive Problem

- n-dimensional data structure, b bins per dimension.
 - Simple binning methods get computationally intensive very, very quickly.
- > You need a binning that is fine enough to catch fine structure in your event distribution.



(you need **lots** of bins)

- The *intrinsic dimensionality* of your problem is reduced because variables may be correlated,
- Thus your problem lives in a subsection of your data structure and many bins are scarcely populated.

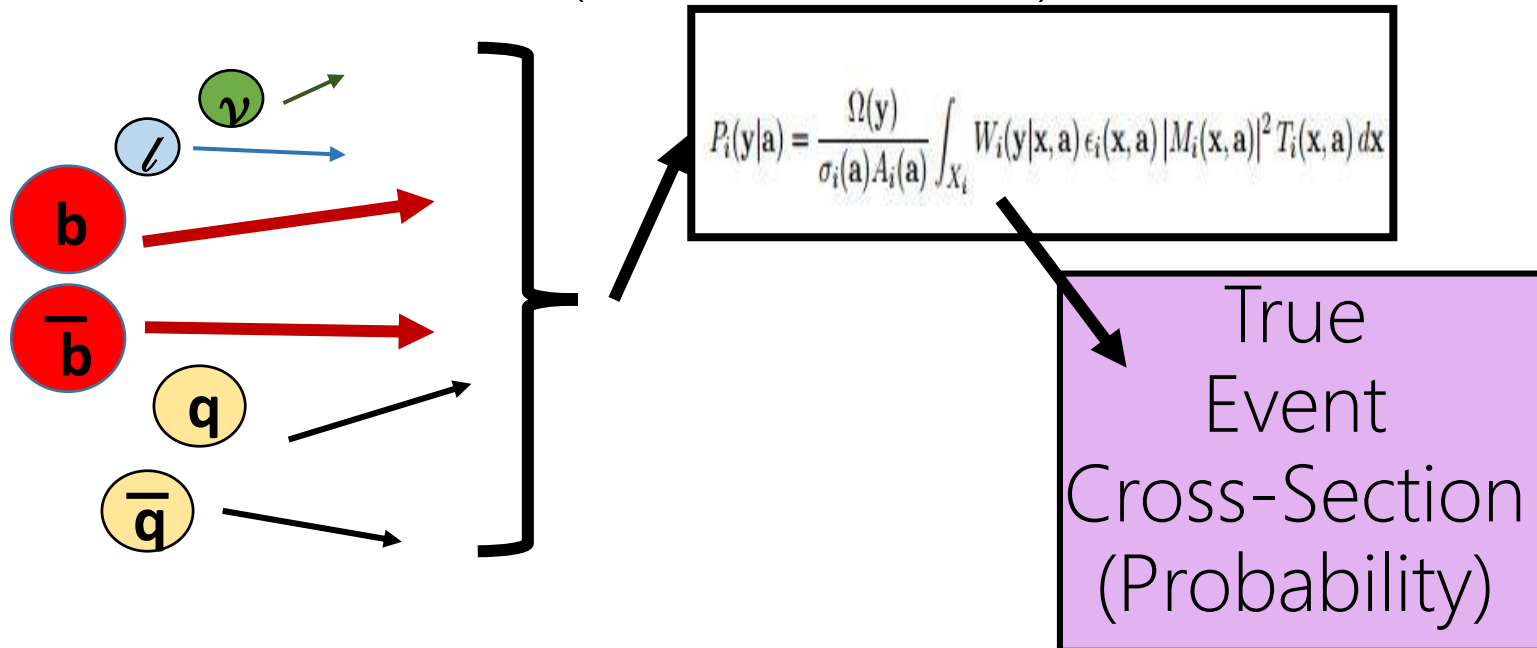
How can we be efficient?

One Solution...

- Self-adaptive binning. Non-equidistant binning in n-dimensions.
...a "Foam" of cells.
- For a given d-dimensional analytically known distribution, the Foam algorithm creates a hyper-rectangular " foam of cells" , which is more dense around the peaks of the distribution and less dense in areas where the distribution is only slowly varying (or flat).
- Iteratively produced using a binary-split algorithm for the cells acting on samplings of the input distribution within the cell boundaries.
- The number of cells is a predefined free parameter.
- A priori, this approach only limited by the amount of available computer memory.
- The optimal number of cells depends on the number of training samples (events used to build the foam).

The "Matrix Element" Method

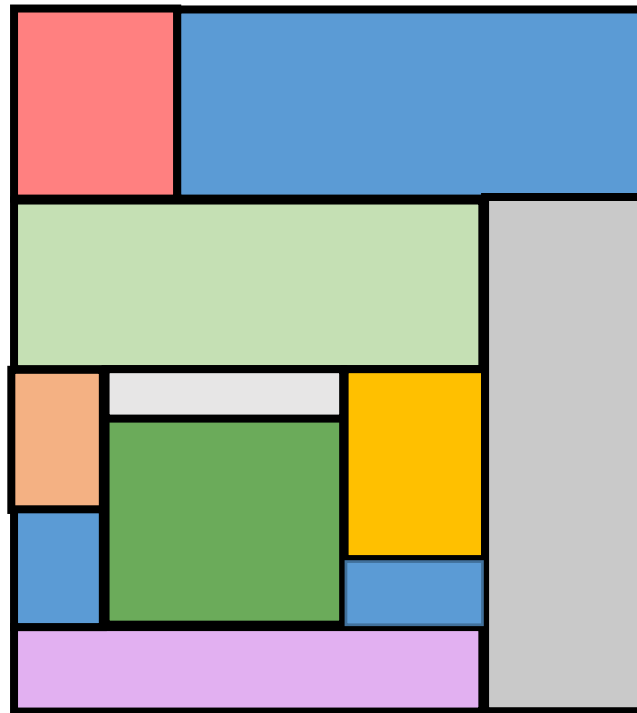
- Introduced by D0 Collaboration, Fermilab, for precision measurement of top quark mass (arXiv: [0406031](#))
- Creates a theoretical matrix element for a decay process in order to compute a probability that this decay was observed for a given set of parameters ([I. Volobouev, arXiv: 1101.2259](#))
- Foam input: A value that uniquely represents the kinematic properties of this event in nature. (Event cross section).



- Strong potential for new physics searches (AMVA4 Workshop, Venice)

PDE Foam

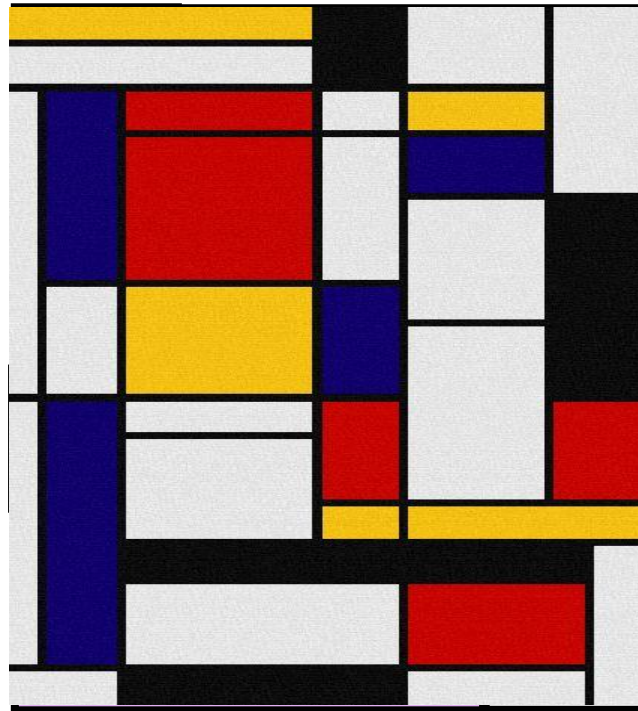
ROOT::PDEFoam is a classification tool that subdivides an n-dim space in bins of constant density. based on ROOT::TFoam for MC integration of analytical functions.



For more information on PDE Foam: D. Dannheim *et al.*, arXiv: [0812.0922](https://arxiv.org/abs/0812.0922)

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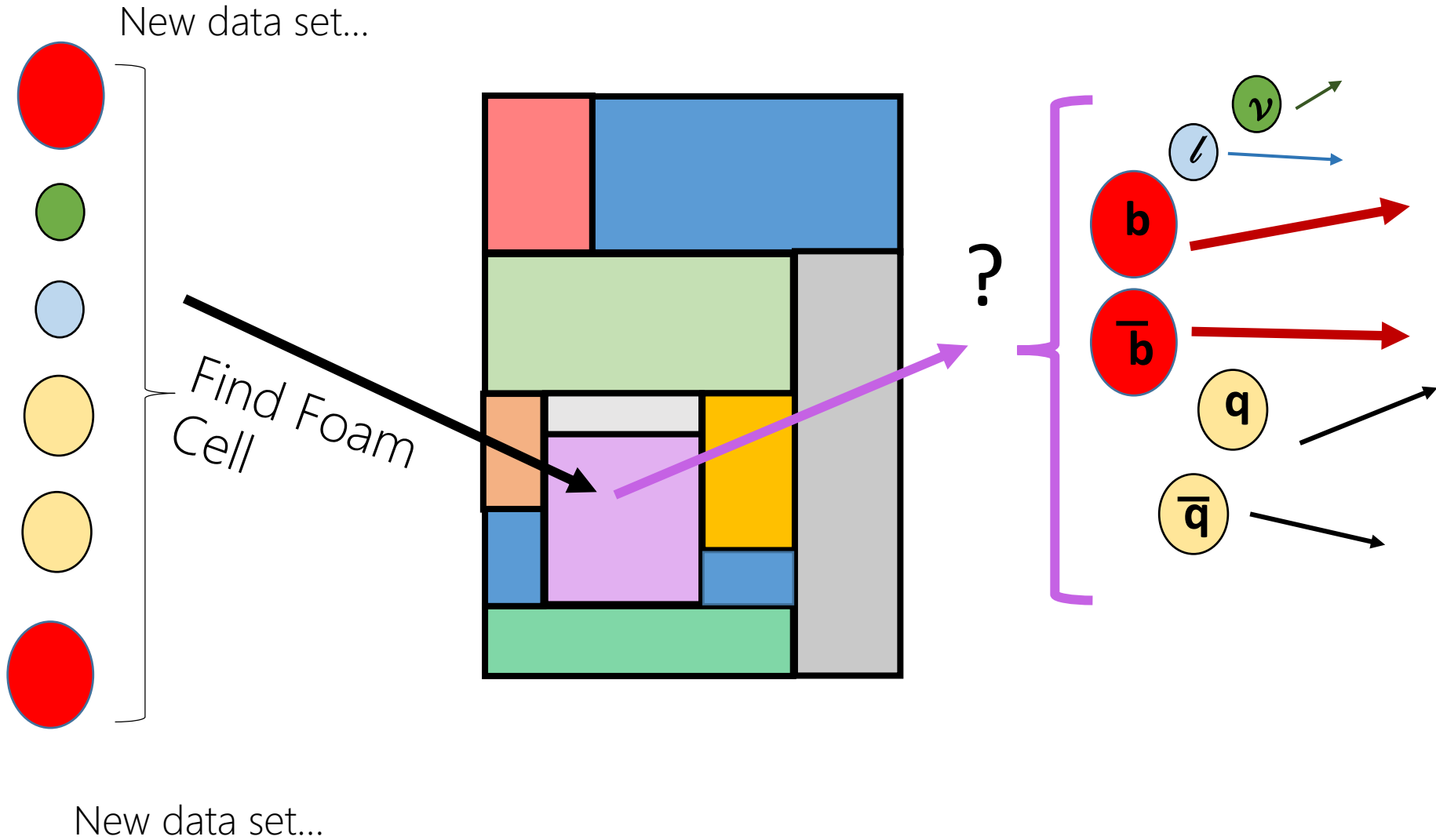


Mondriaan was definitely onto something...

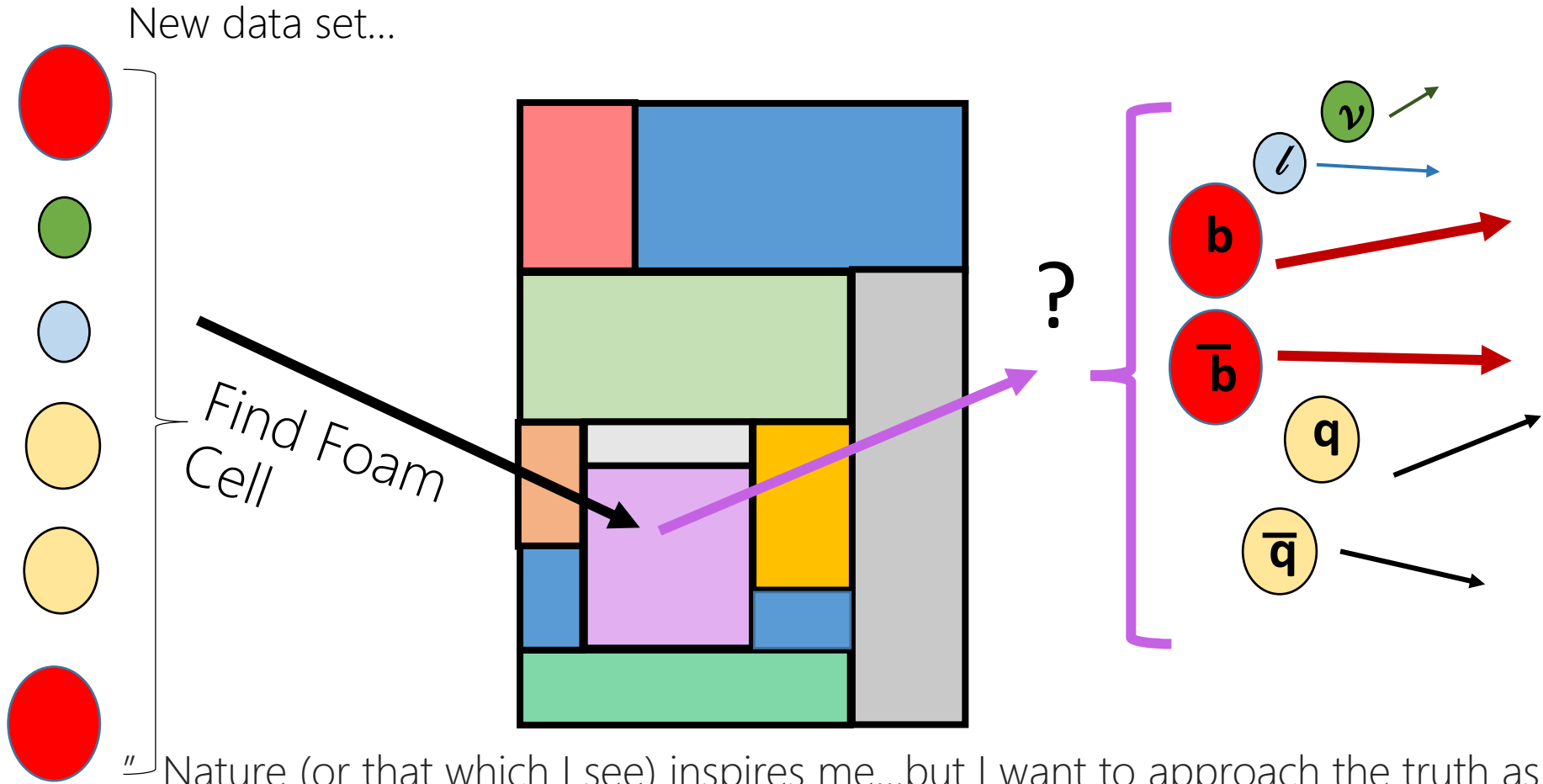
...Who says art can't inspire science?

For more information on PDE Foam: D. Dannheim *et al.*, arXiv: [0812.0922](https://arxiv.org/abs/0812.0922)

Kinematic Reconstruction



Kinematic Reconstruction



"Nature (or that which I see) inspires me...but I want to approach the truth as closely as possible, abstracting everything until I come to the foundation...."

• In a letter to [H. P. Bremmer](#), Paris 29 January 1914; ; as quoted in *Mondrian, - The Art of Destruction*, Carel Blotkamp,

Trial Run... 1 Dimension

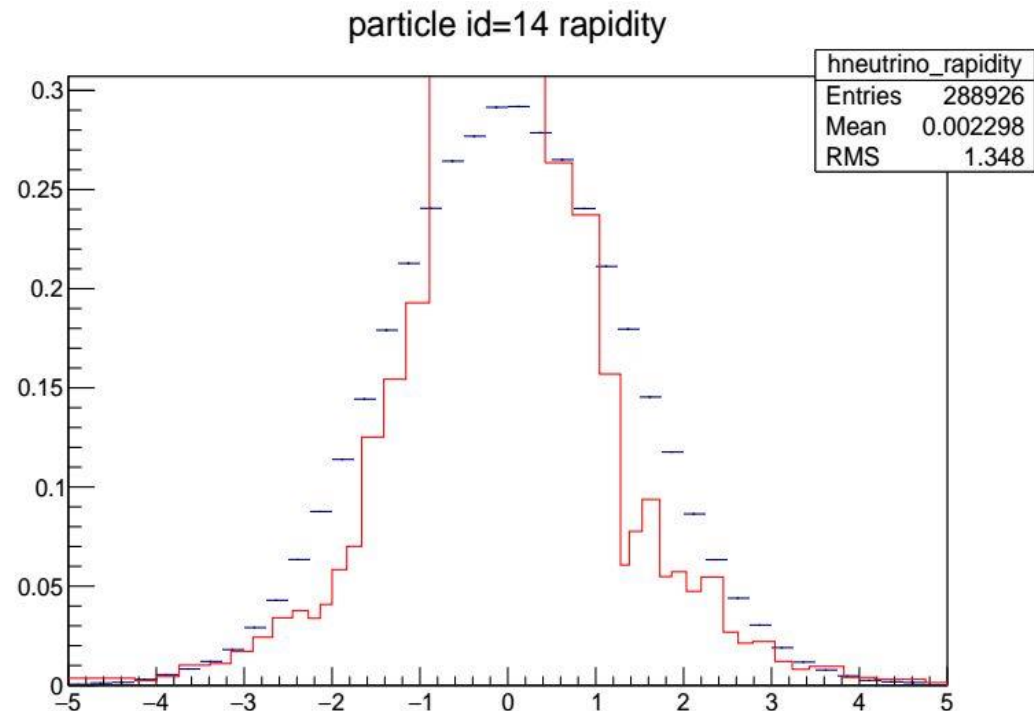
- Investigations have started using Sherpa in fixed order QCD mode
- (Only using leading order (LO) for the moment)

Example

- $5 \cdot 10^5$ events
- 1 Dimension, rapidity of 1 particle

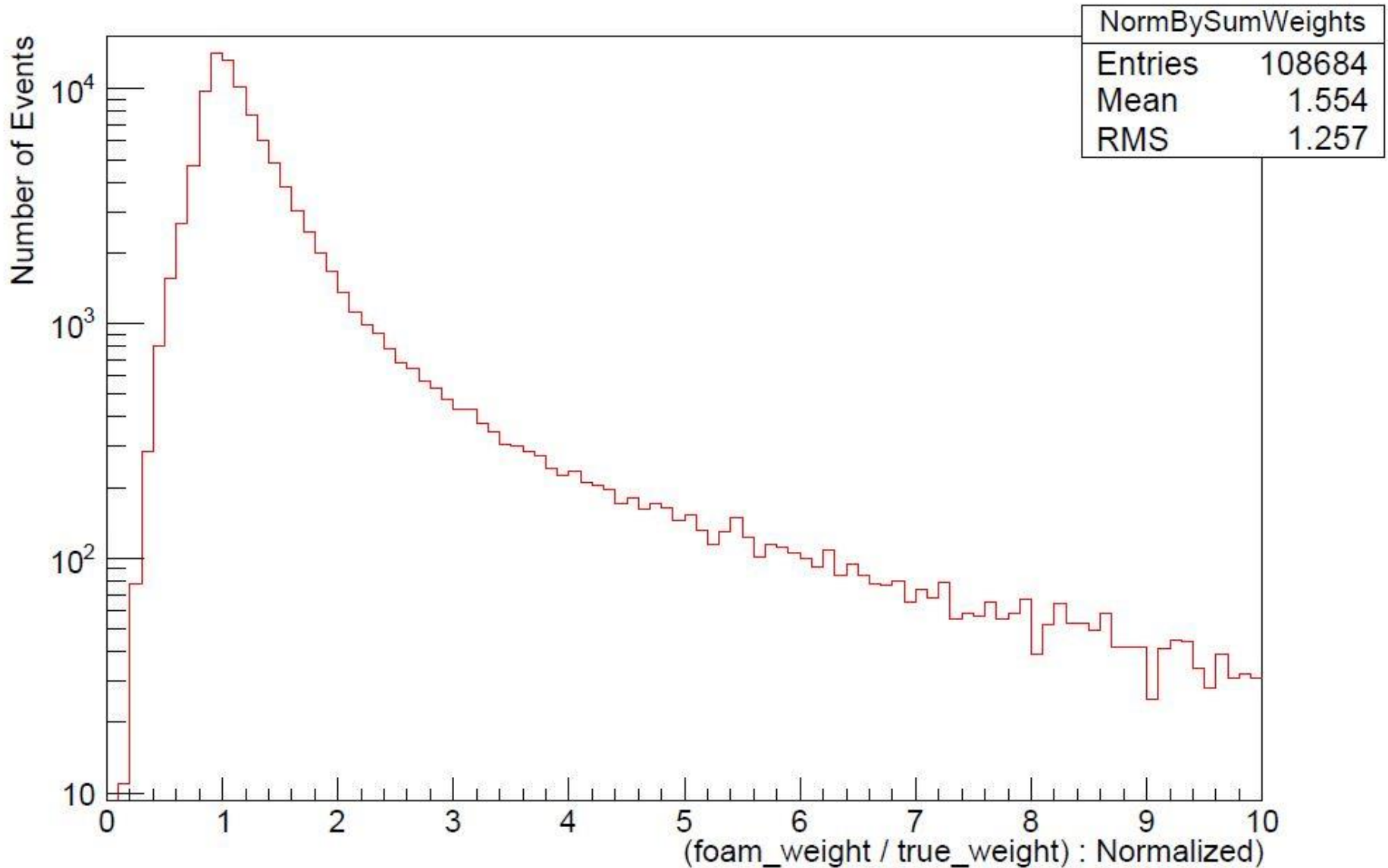
Challenges

- Interpreting foam performance (comparing reference histogram to foam output)
- Correctly dividing by bin width has proven to be non-trivial.



15 Dimension Success

Foam Performance: Ration of Normalized Foam Weight to Normalized Sherpa File Weight



Foam -Weighted True Configuration m_{top}

