To Emulate or to Differentiate? A Delphes3 optimization study

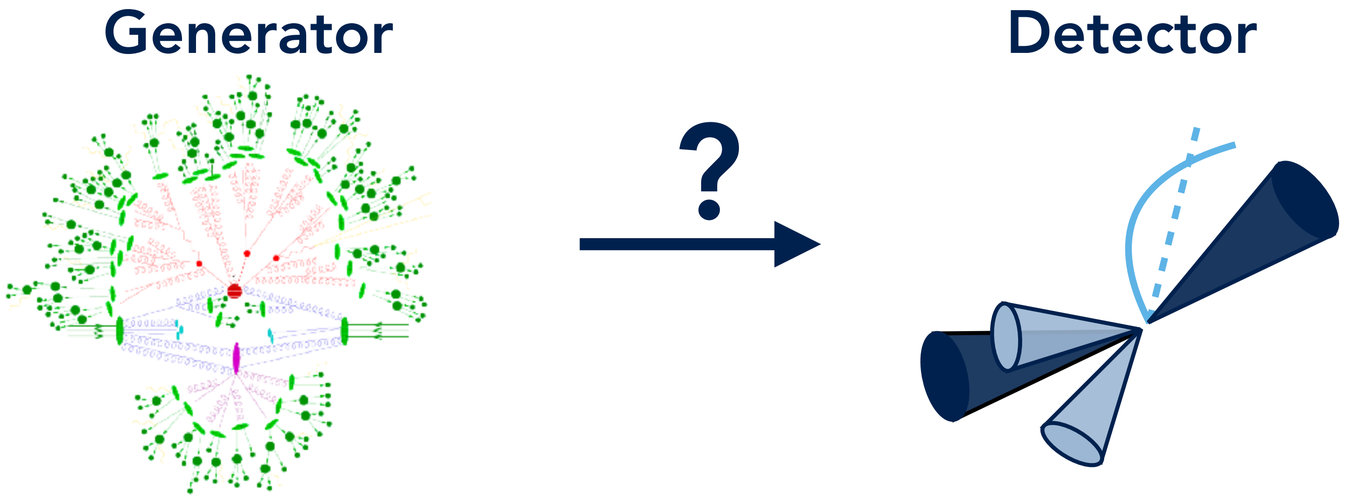
Luigi Favaro, Andrea Giammanco

15.09.2026

ML4Jets26

Vienna

End-to-end simulation



Motivations:

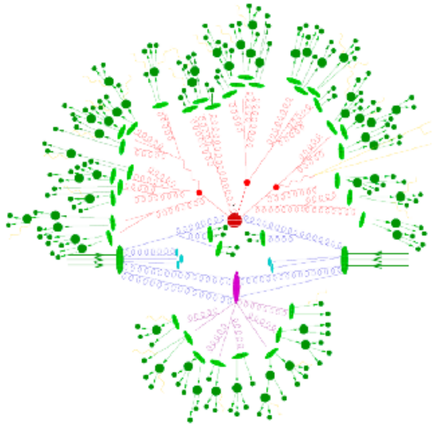
Compact and accurate representation of detectors

Publicly available to the community

Simulation and storage cost of full simulations

End-to-end simulation

Generator



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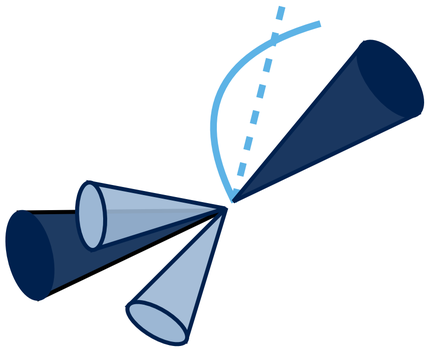
Detector



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(electrons, muons, photons, jets)

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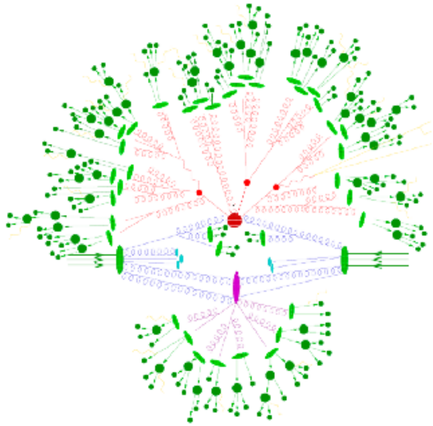

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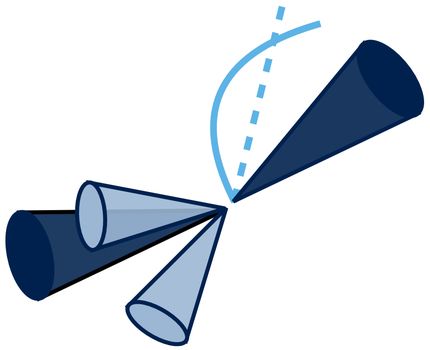

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Delphes3 is a great example of modularised and simple detector modelling

To emulate or to differentiate?

Setting:

Access to paired data, CMS open data full sim Drell-Yan + 3 jets

Distance-based matching between gen. and reco. objects

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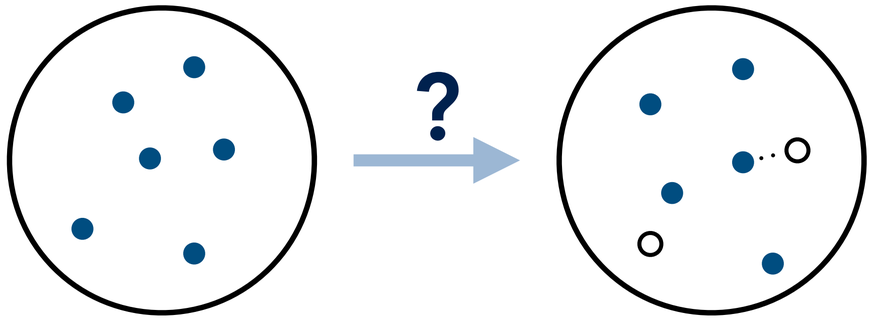
Matching:

- distance-based matching: $\Delta R < R_{\text{max}}$
- p_T matching: $p'_T/p_T < r$
- exclusive selection



Data allows to use any other matching scheme

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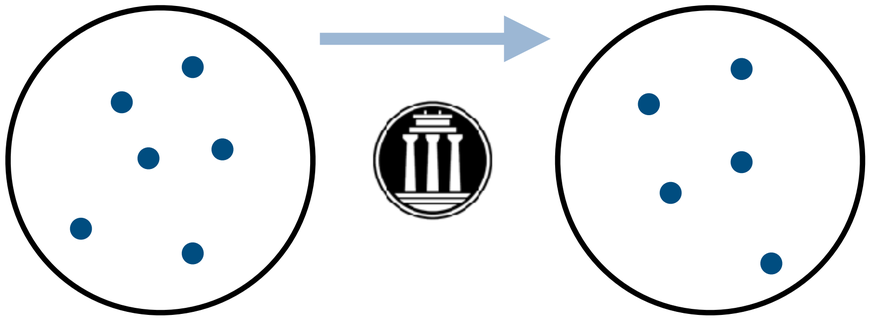
Differentiable simulator:



Physics model
with access to gradients $\partial\mathcal{L}/\partial$

Turn Delphes into a differentiable simulator*:

- no hand tuning of detector cards
- directly differentiate through the simulator

*similar work done with Parnassus in 2608.22873, A. Elabd et al.

To emulate or to differentiate?

Setting:

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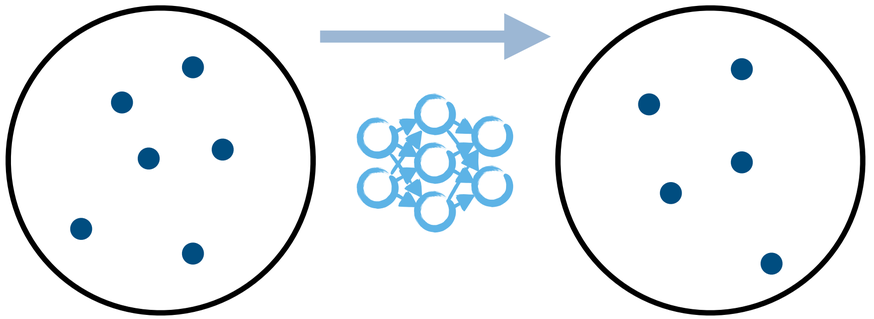
Generative network trained on paired data:

- removes limitations from simple detector cards

Generative emulator:



Neural network encodes $p(x_{\text{reco}} \mid x_{\text{gen}})$

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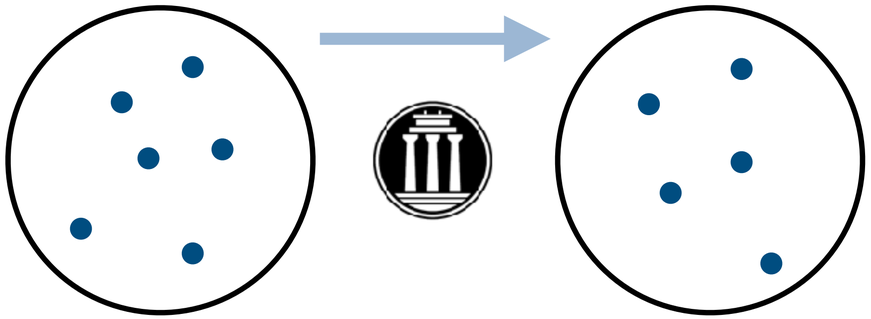

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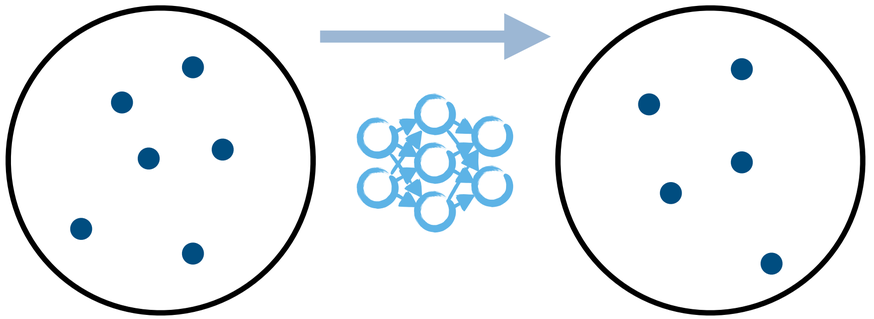

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Differentiable Delphes

HEPMC data

Step 1: reimplement Delphes in PyTorch

Differentiable Delphes

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Tracker:
apply smearing and efficiency to

- charged hadrons
- electrons
- muons

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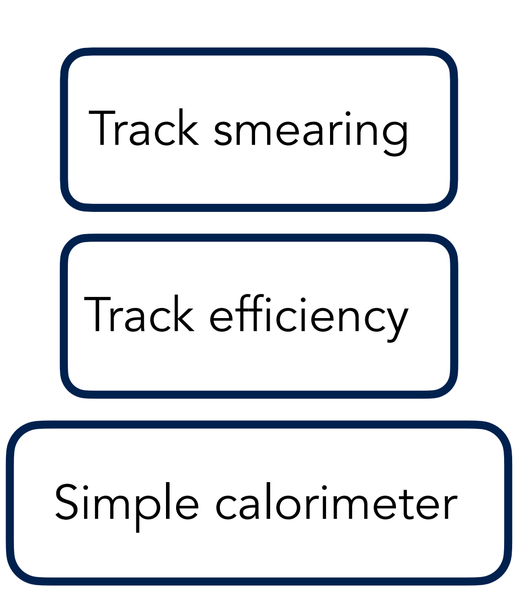
Calorimeter:
define and apply smearing to energy towers in ECal and HCal



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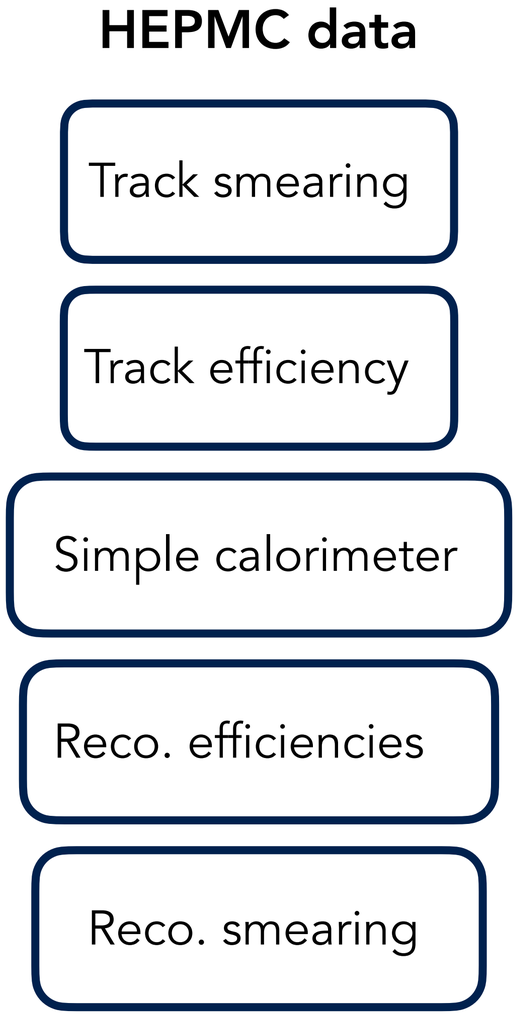
Efficiency and isolation for electrons, photons, and muons



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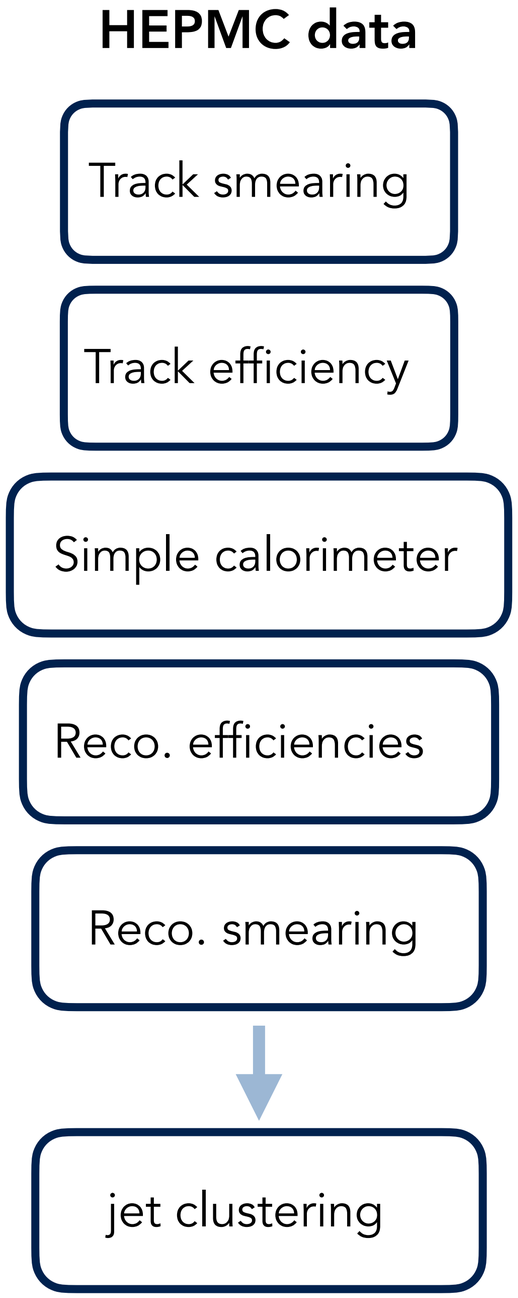

Differentiable Delphes

Step 1: reimplement Delphes in PyTorch

Step 2: block parametrizations

Smearing functional form: Log-Normal distribution

$$\sigma_{\text{res}}(p_T, \eta) = \sqrt{\theta_0(\eta)^2 + \theta_1(\eta)^2 p_T^2}$$

(total of 18 smearing parameters)

Delphes default (pre-fit)

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Example momentum smearing

```
# resolution formula for muons
set ResolutionFormula {                    (abs(eta) <= 0.5) * (pt > 0.1) * sqrt(0.01^2 + pt^2*1.0e-4^2) +
                       (abs(eta) > 0.5 && abs(eta) <= 1.5) * (pt > 0.1) * sqrt(0.015^2 + pt^2*1.5e-4^2) +
                       (abs(eta) > 1.5 && abs(eta) <= 2.5) * (pt > 0.1) * sqrt(0.025^2 + pt^2*3.5e-4^2)}
}
```

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Example momentum smearing

```
# resolution formula for muons
set ResolutionFormula {
              (abs(eta) <= 0.5) * (pt > 0.1) * sqrt(0.0088232^2 + pt^2*0.00012419^2) +
              (abs(eta) > 0.5 && abs(eta) <= 1.5) * (pt > 0.1) * sqrt(0.014642^2 + pt^2*0.00014692^2) +
              (abs(eta) > 1.5 && abs(eta) <= 2.5) * (pt > 0.1) * sqrt(0.022765^2 + pt^2*0.00036676^2)}
}
```

Differentiable Delphes

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Efficiency functional form: surviving probability

$$q(x;\theta) = \begin{cases} x & \text{if} \quad a < \theta \\ 0 & \text{if} \quad a > \theta \end{cases} \qquad \text{where} \quad a \sim \mathcal{U}(0,1), \theta \in [0,1)$$

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Delphes default (pre-fit)

Example efficiencies

```
# efficiency formula for electrons
set EfficiencyFormula {                                          (pt <= 10.0) * (0.00) +
                                        (abs(eta) <= 1.5) * (pt > 10.0)  * (0.95) +
                       (abs(eta) > 1.5 && abs(eta) <= 2.5) * (pt > 10.0)  * (0.85) +
                       (abs(eta) > 2.5)                                   * (0.00)}
}
```

Differentiable Delphes

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Efficiency functional form: surviving probability

$$q(x;\theta,p_T) = \theta_0(1+\theta_1\log(p_T))$$

2 learnable parameters (post-fit)

Free to use more complex cards

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Example efficiencies

```
set EfficiencyFormula {
  (abs(eta) <= 0.5) * (0.98154*(1.0 + (+0.008235)*log(pt/50.0))) + \
  (abs(eta) > 0.5 && abs(eta) <= 1.0) * (0.98485*(1.0 + (+0.008649)*log(pt/50.0))) + \
  (abs(eta) > 1.0 && abs(eta) <= 1.5) * (0.97318*(1.0 + (+0.046652)*log(pt/50.0))) + \
  (abs(eta) > 1.5 && abs(eta) <= 2.0) * (0.97574*(1.0 + (+0.034300)*log(pt/50.0))) + \
  (abs(eta) > 2.0 && abs(eta) <= 2.5) * (0.96812*(1.0 + (+0.069869)*log(pt/50.0))) + \
  (abs(eta) > 2.5 && abs(eta) <= 5) * ((pt > 0.5) * (0.92506 * (1.0 + (-0.042945) * log(pt/50))
  (abs(eta) > 5) * (0.00)
}
```

Differentiable Delphes

Step 1: reimplement Delphes in PyTorch

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Step 3: optimization

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Efficiency: Bernoulli likelihood

$$\mathscr{L}_{\text{eff}}(\theta) = \left\langle x \log q(x;\theta) + (1-x)\log(1-q(x;\theta)) \right\rangle_{x\sim p_{\text{data}}}$$

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Smearing: Log-Normal likelihood

$$\mathscr{L}_{\text{smear}}(\theta) = \left\langle \frac{1}{2}\log(2\pi b^2) + \frac{(\log(x'(\theta)/x) + b^2/2)^2}{2b^2} \right\rangle_{x\sim p_{\text{data}}} \qquad b^2 = \log(1+\sigma^2_{\text{res}}(\theta))$$

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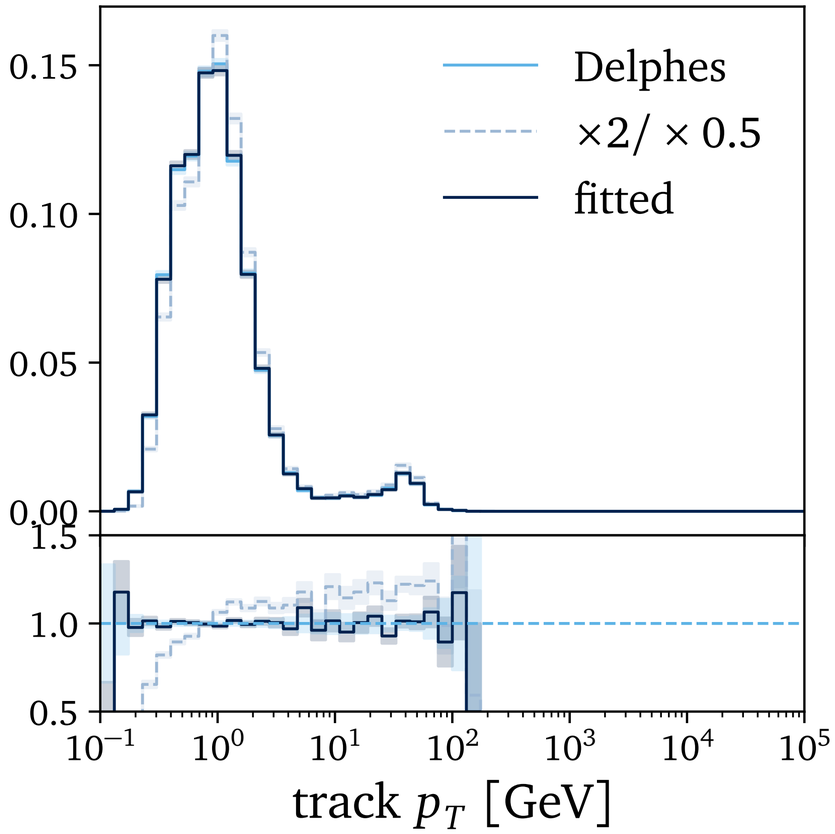
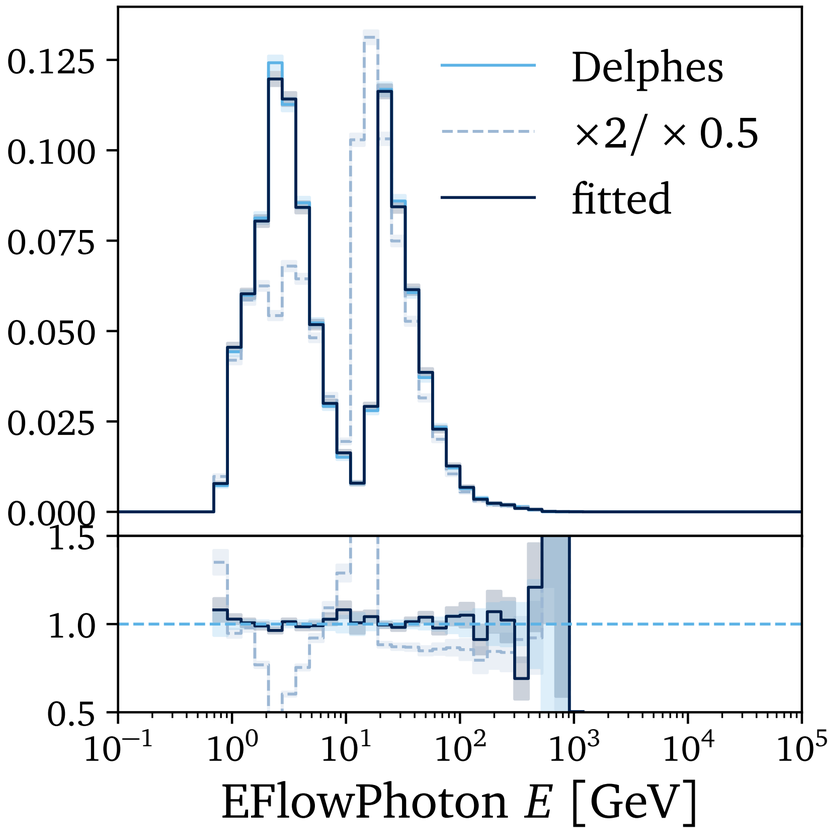
The optimization is a maximum likelihood estimate (MLE): negative log-likelihood loss*

$$\mathscr{L}_{\text{joint}} = \sum_{\text{species}} \mathscr{L}_{\text{eff}} + \mathscr{L}_{\text{smear}}$$

*when intermediate states are available

Delphes closure tests



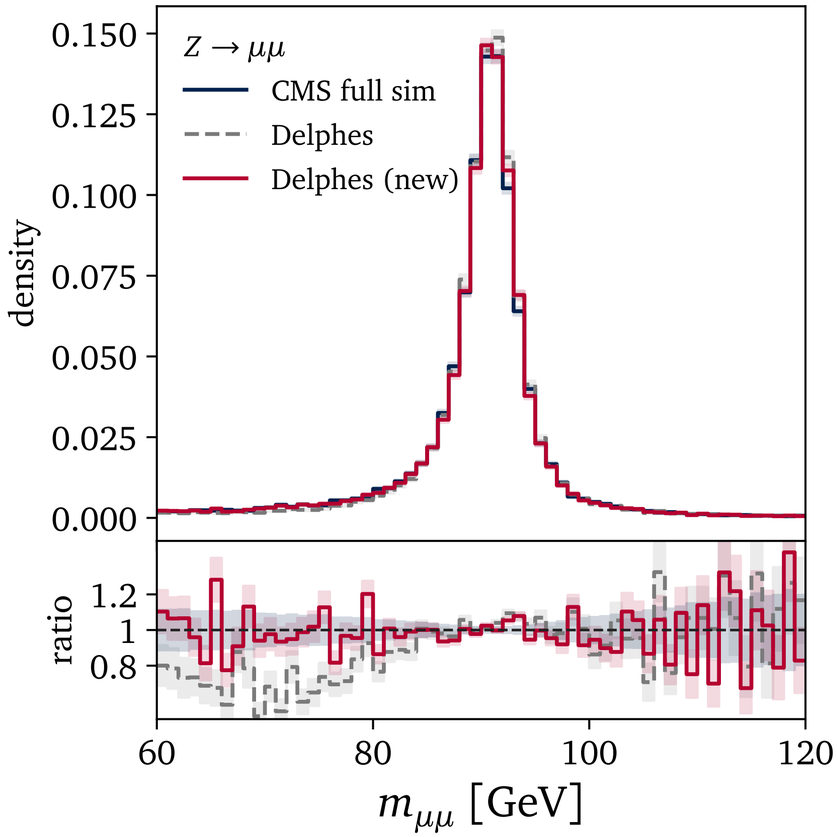


Applied to DY events generated with MG5+Pythia+Delphes:

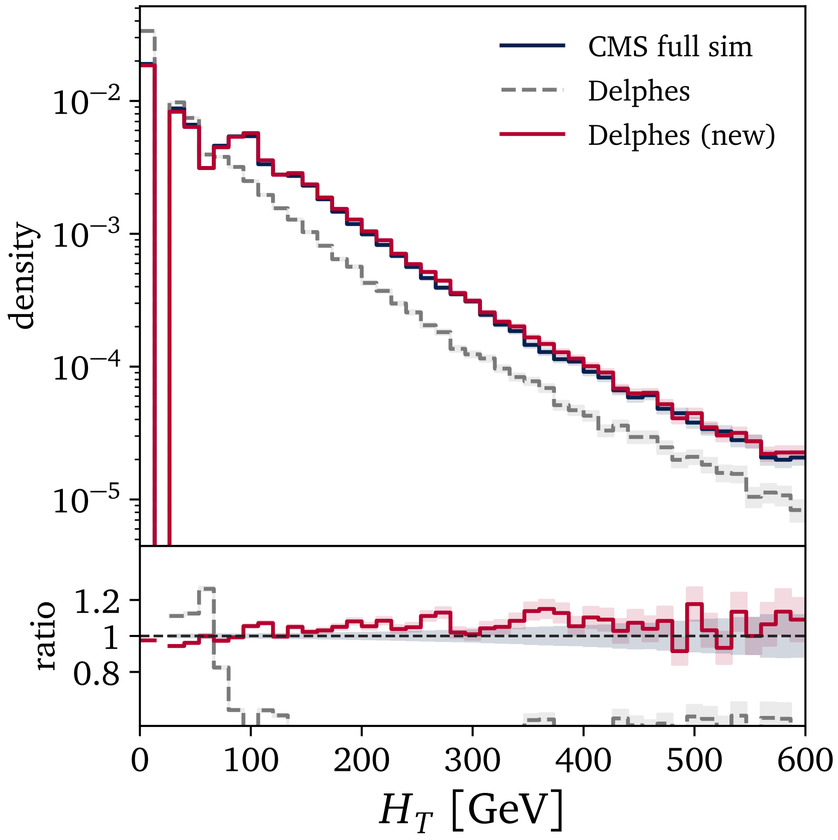
we correctly recover the original values of the Delphes card

CMS full sim DY

Downstream observables



dimuon mass



jets transverse momentum

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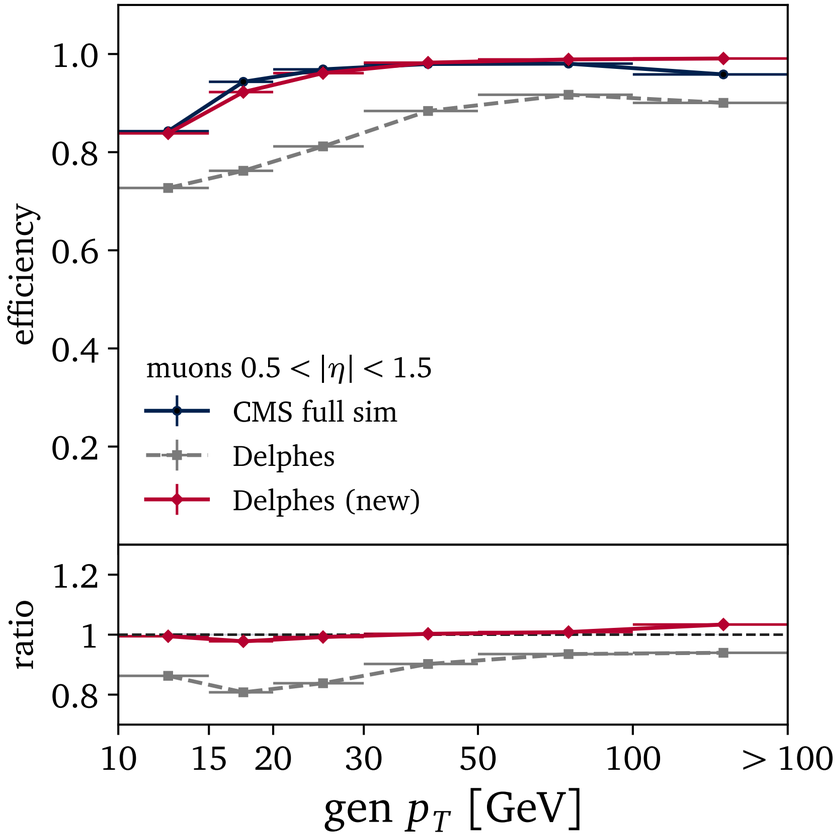
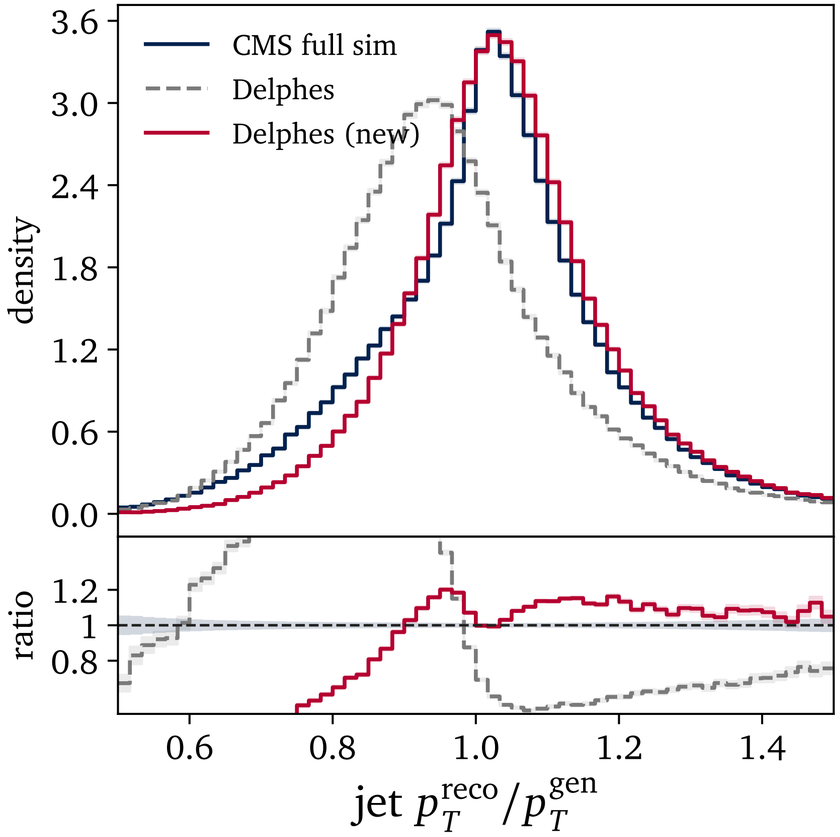


muon efficiency



jet smearing

Limitations due to the simple card functional form

Generative Delphes

Emulate the detector response through a generative network

Generator-level Inputs:

- for each generated object: $\{\log p_T, \eta, \sin\phi, \cos\phi, m\}$
- object type: electron, muon, photon, jet
- event-level input: number of objects, MET, H_T

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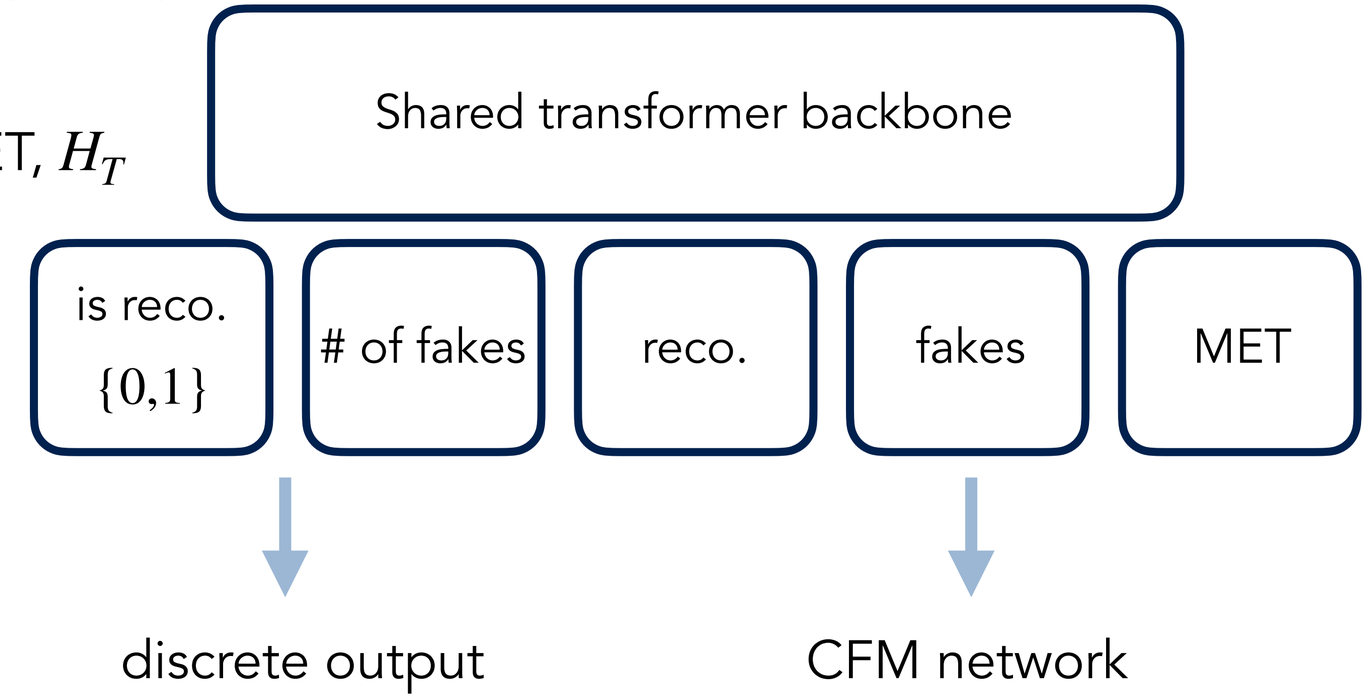
Generated quantities:

- # of unmatched and reco. objects
- kinematics: $\{\log p_T, \eta, \sin\phi, \cos\phi, m\}$ of reco., fakes, and MET



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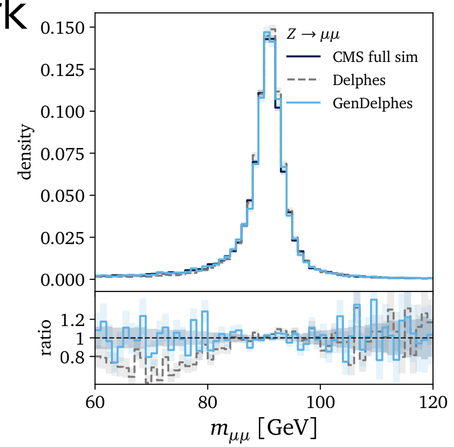

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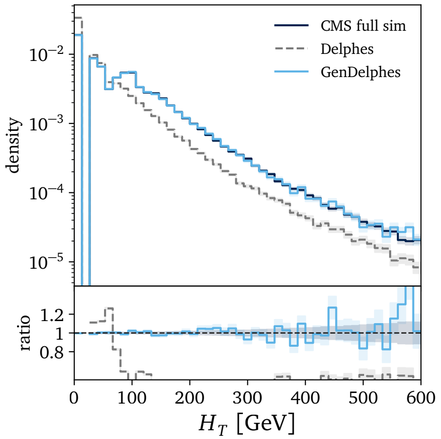
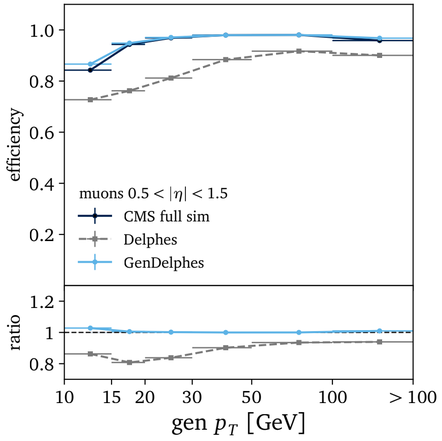
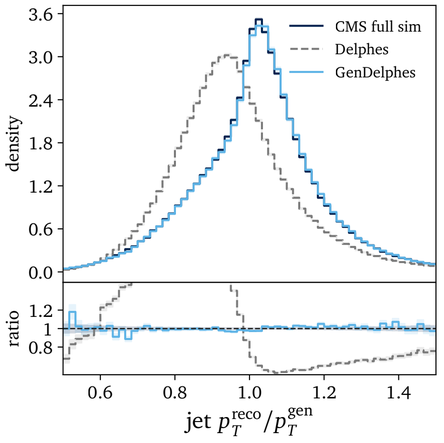


jets transverse momentum



muon efficiency



jet smearing

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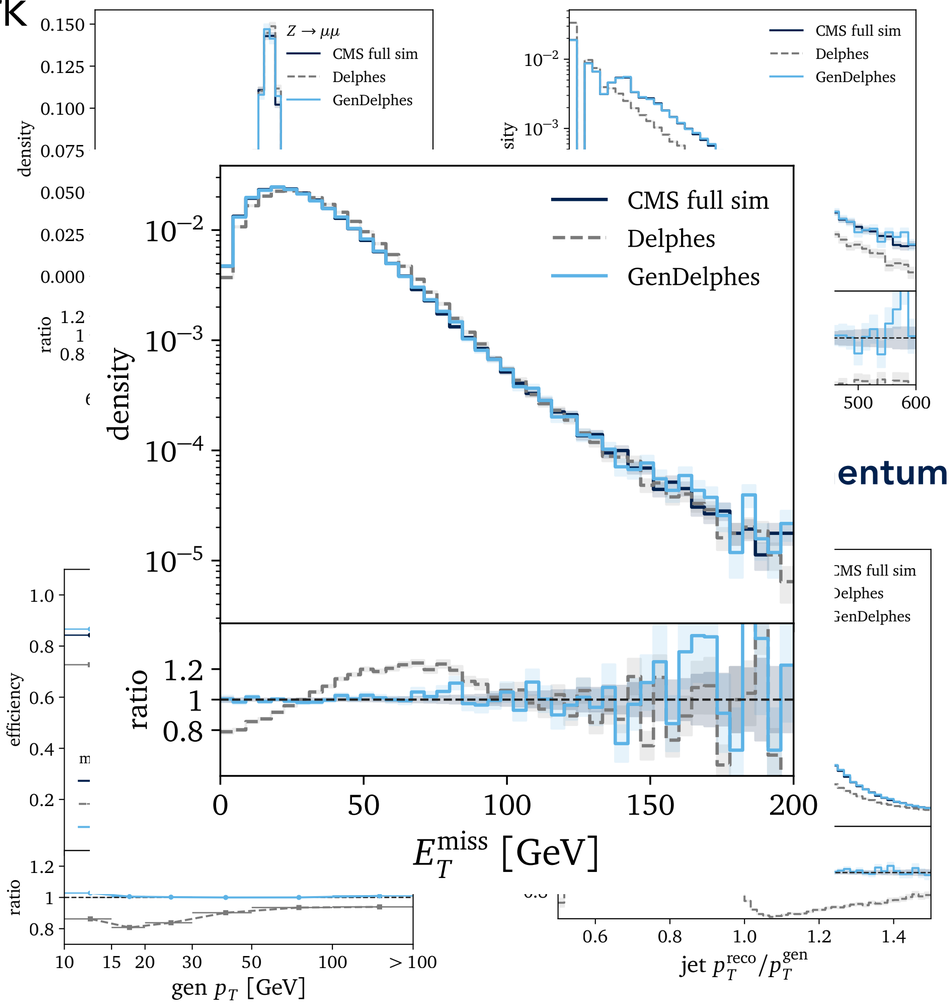


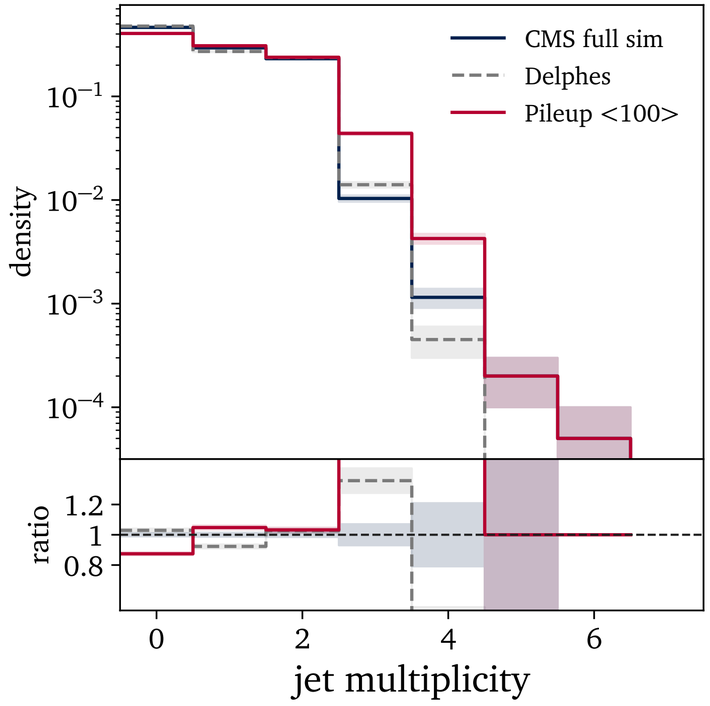
entum

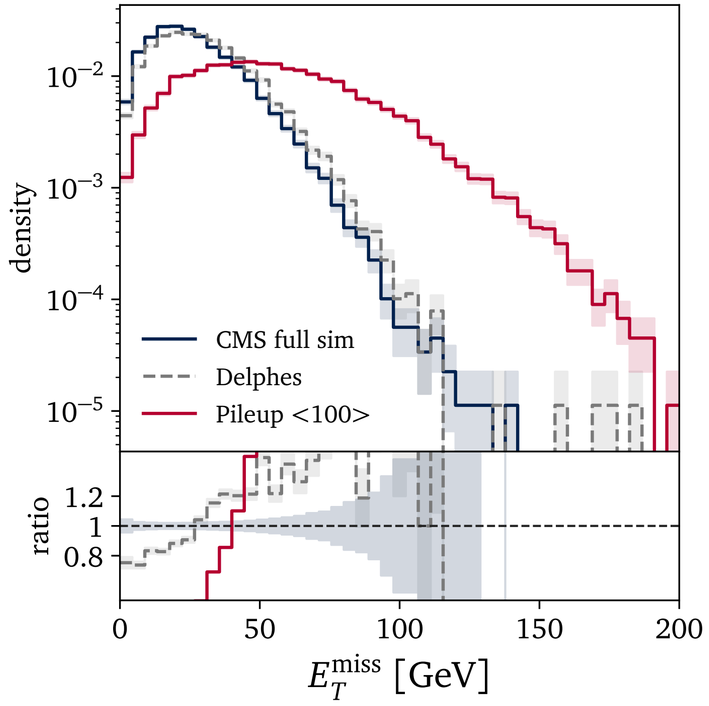
muon efficiency

jet smearing

Pileup

Delphes has a pileup model ⟶ it can be varied (set by $\langle\mu\rangle$)





A generative network uses the pileup seen in the training data ($< 25 >$)

Conclusions/Outlook

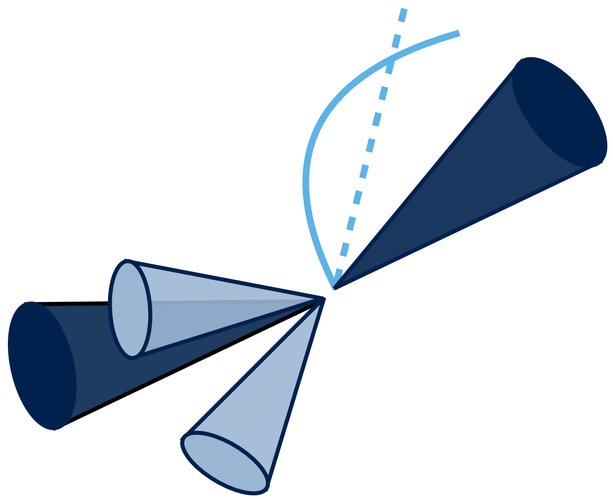
Emulation and differentiation are two approaches to solve the same problem

Differentiate:

- make use of already efficient simulators
- simple and portable: new detector cards can be effortlessly deployed
- interpretable: explicit smearing formulas and efficiencies
- fastest

Emulate:

- best agreement with CMS full sim
- still fast (on GPU)



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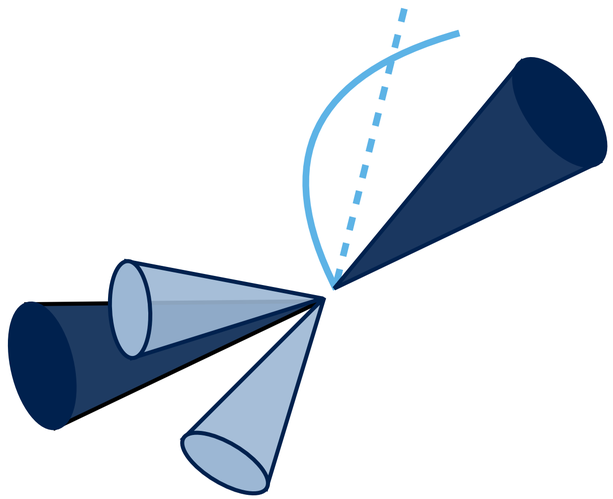

Good reconstruction of downstream DY observables in both case

Pileup is treated differently

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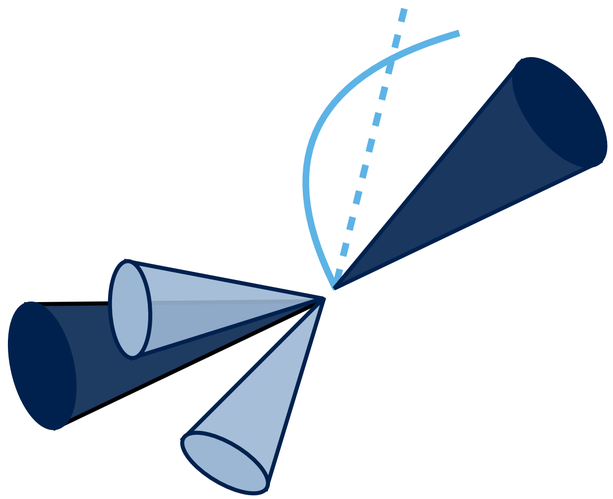
- best agreement with CMS full sim
- still fast (on GPU)



Good reconstruction of downstream DY observables in both case

Pileup is treated differently

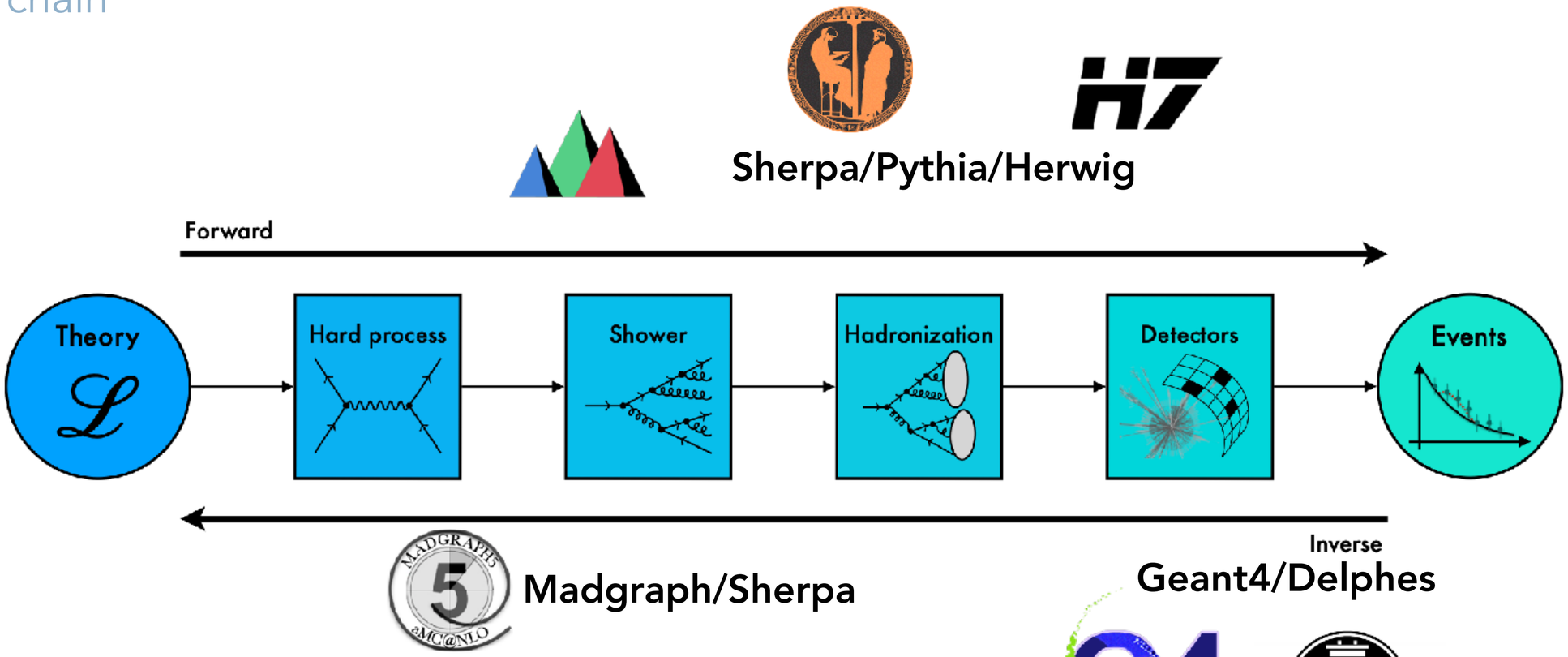
A lot of new ideas and discussions with Parnassus, stay tuned!

Thanks for your attention!

Backup

Context

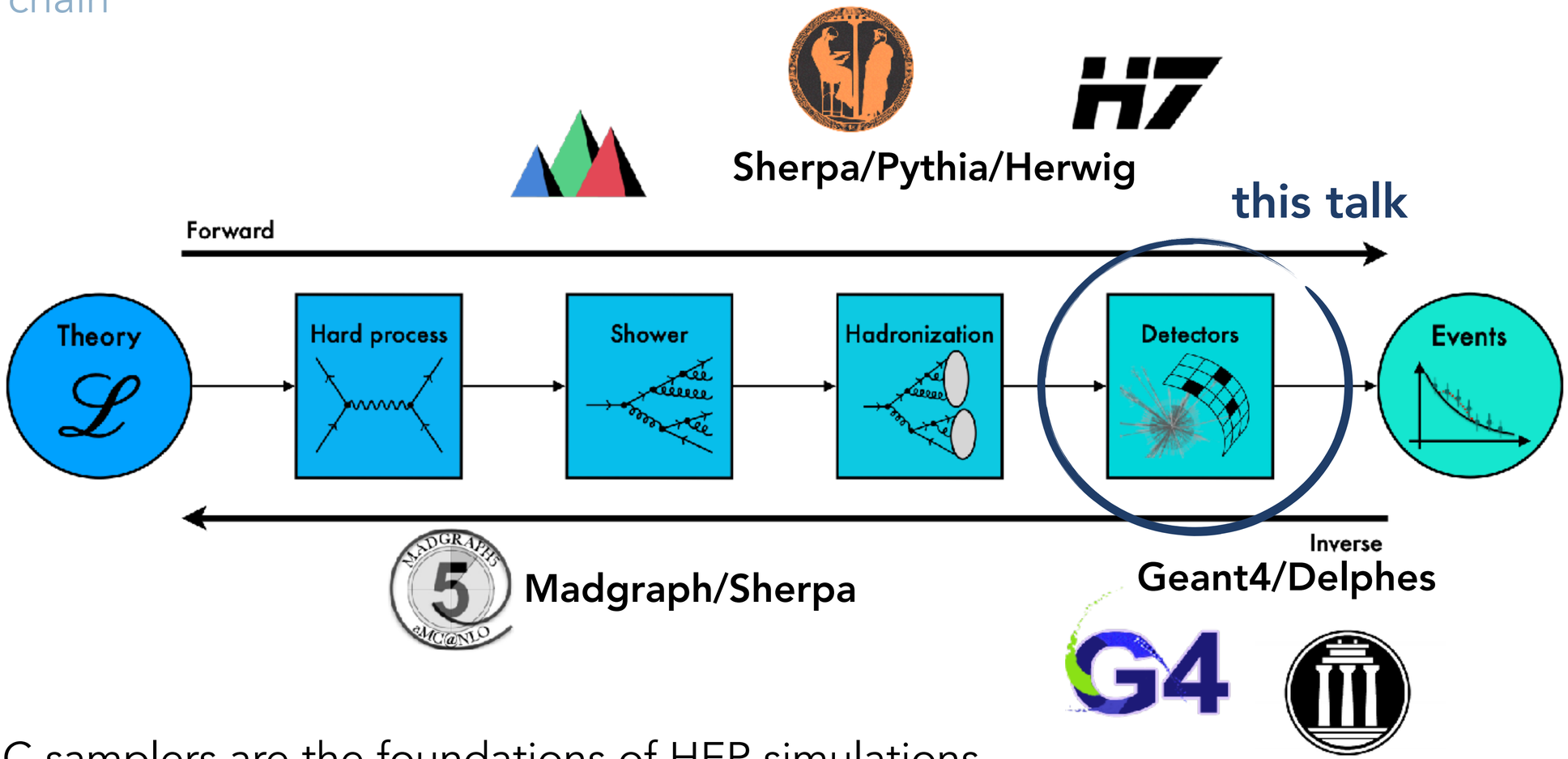
Simulation chain



- MCMC samplers are the foundations of HEP simulations.

Context

Simulation chain

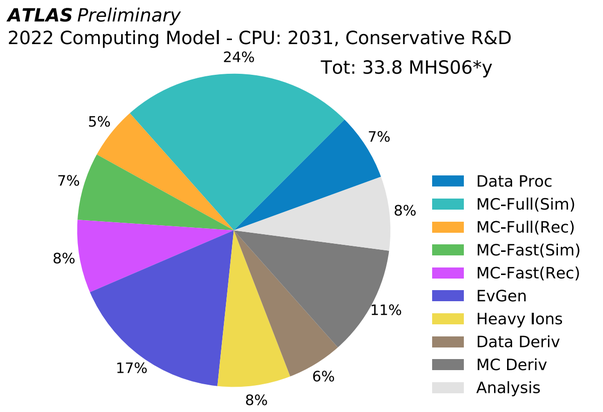


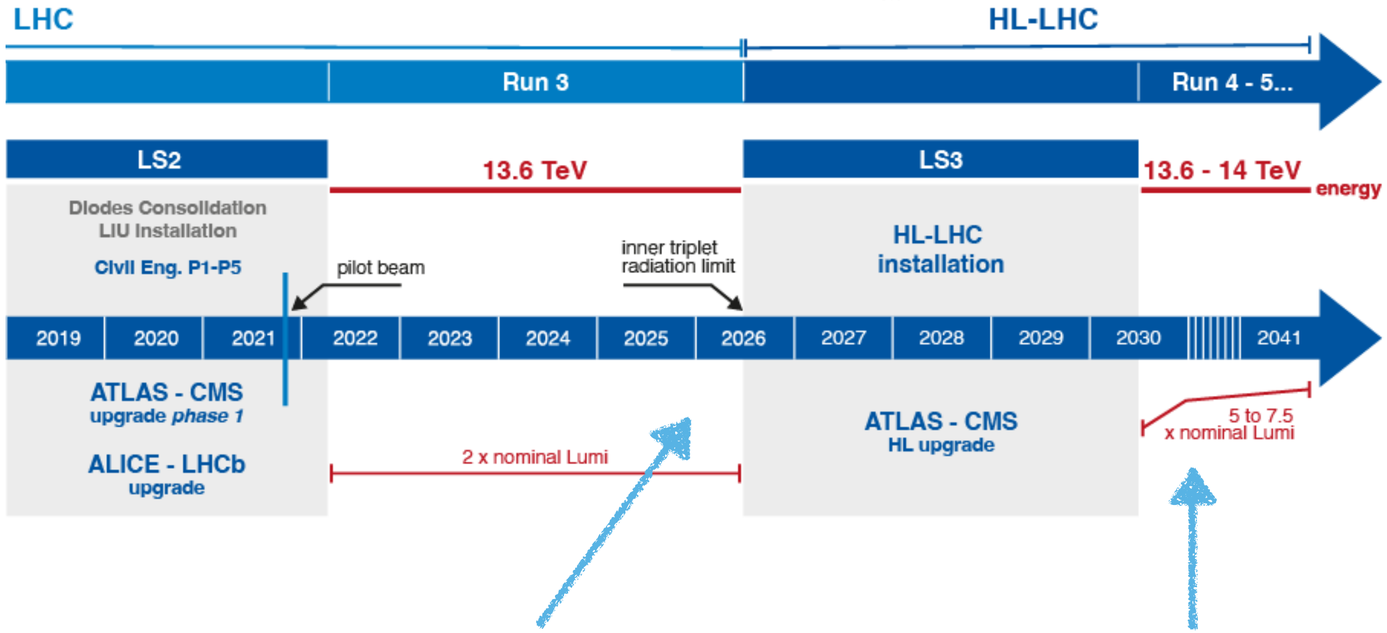
- MCMC samplers are the foundations of HEP simulations.

Context

Challenges

- High-Luminosity LHC will produce unmatched amount of data;
- simulations need to match the collected statistics.





2026: end of Run3 **~3x increase in luminosity**

Context

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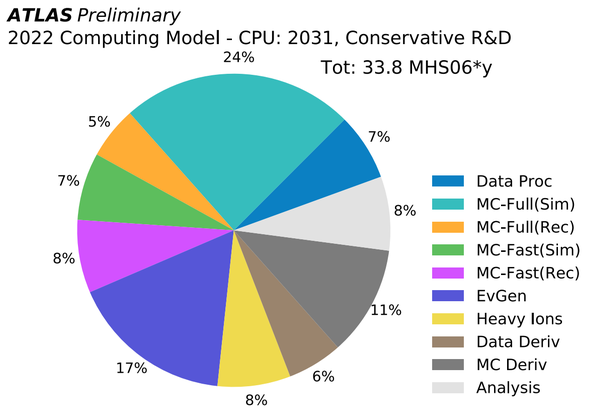
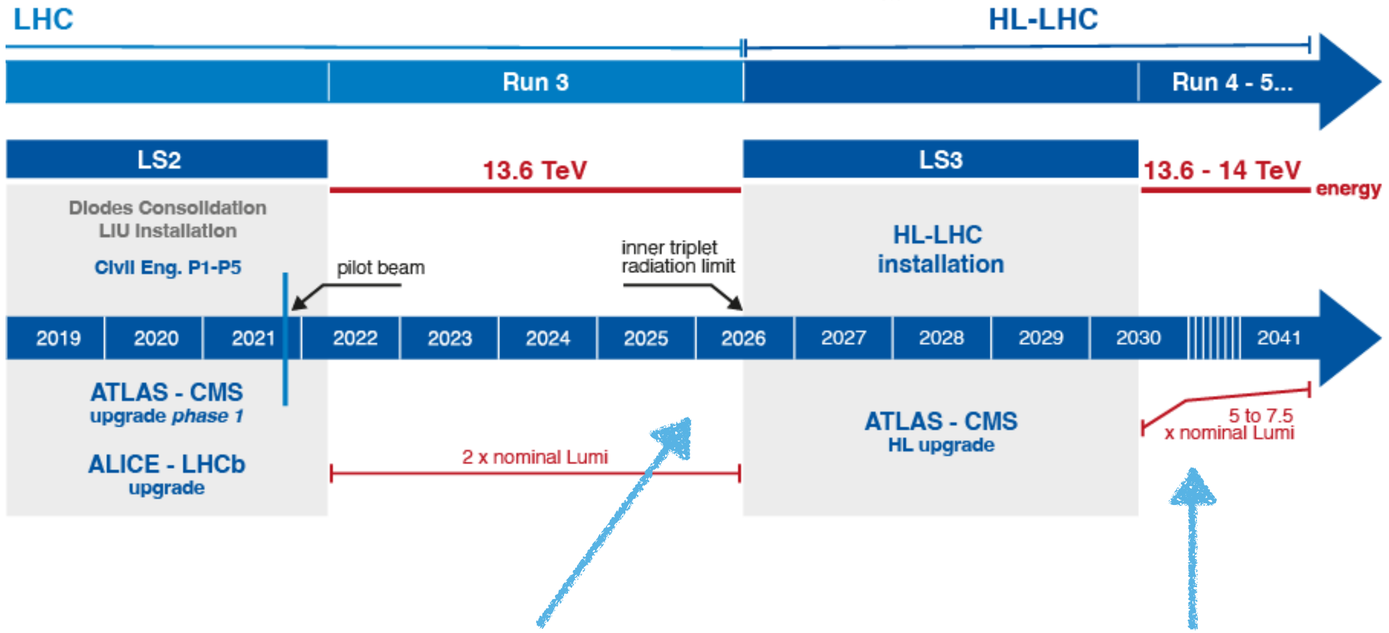


Overarching goal:

Maximise LHC potential

- find BSM physics;
- understand LHC data w/ SM.

Requires better and faster simulators



2026: end of Run3 **~3x increase in luminosity**

CMS full sim evaluation

More validation plots