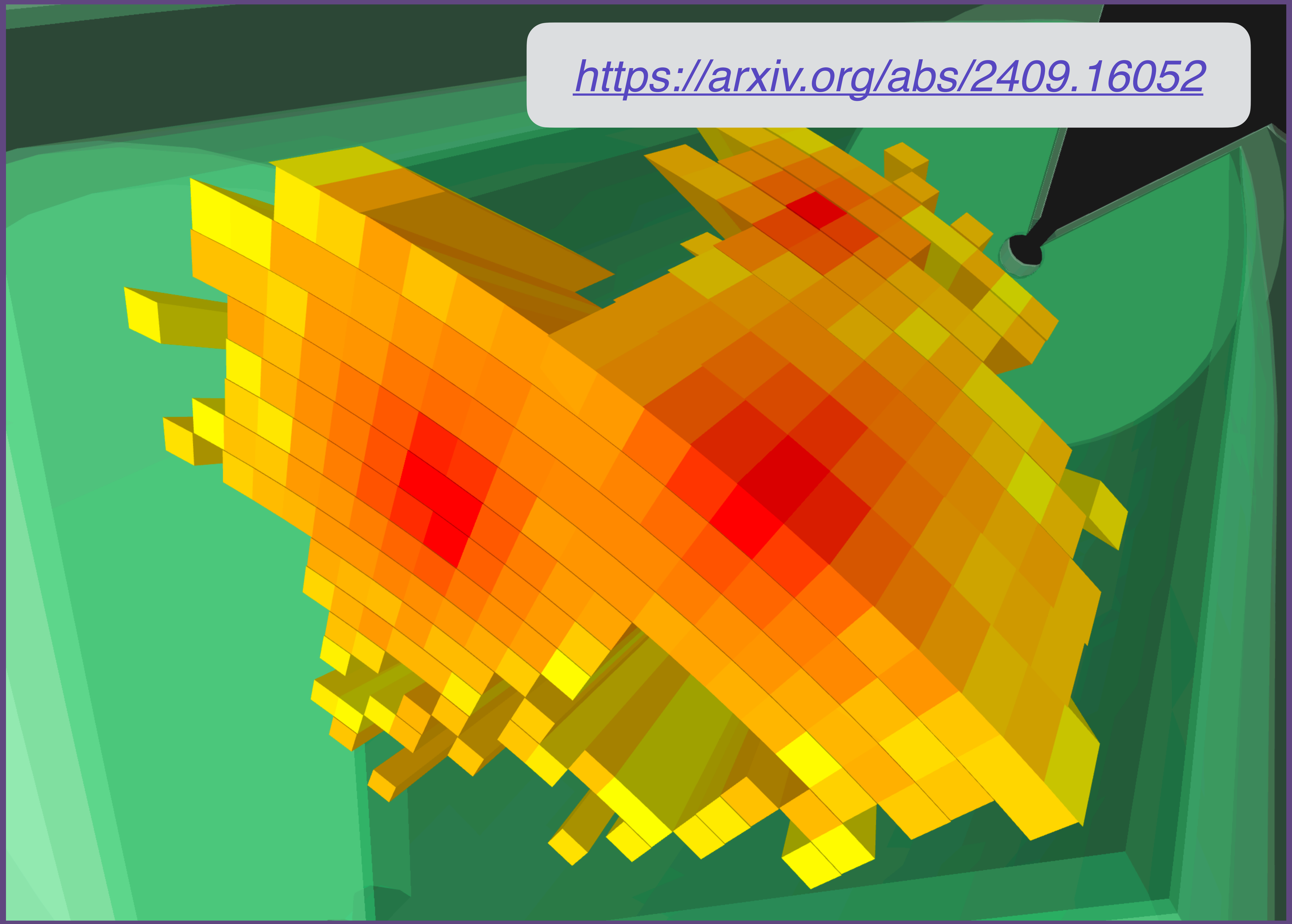
Denoising Graph Super-Resolution for Improved Collider Event Reconstruction

ML4Jets
06 November, 2024

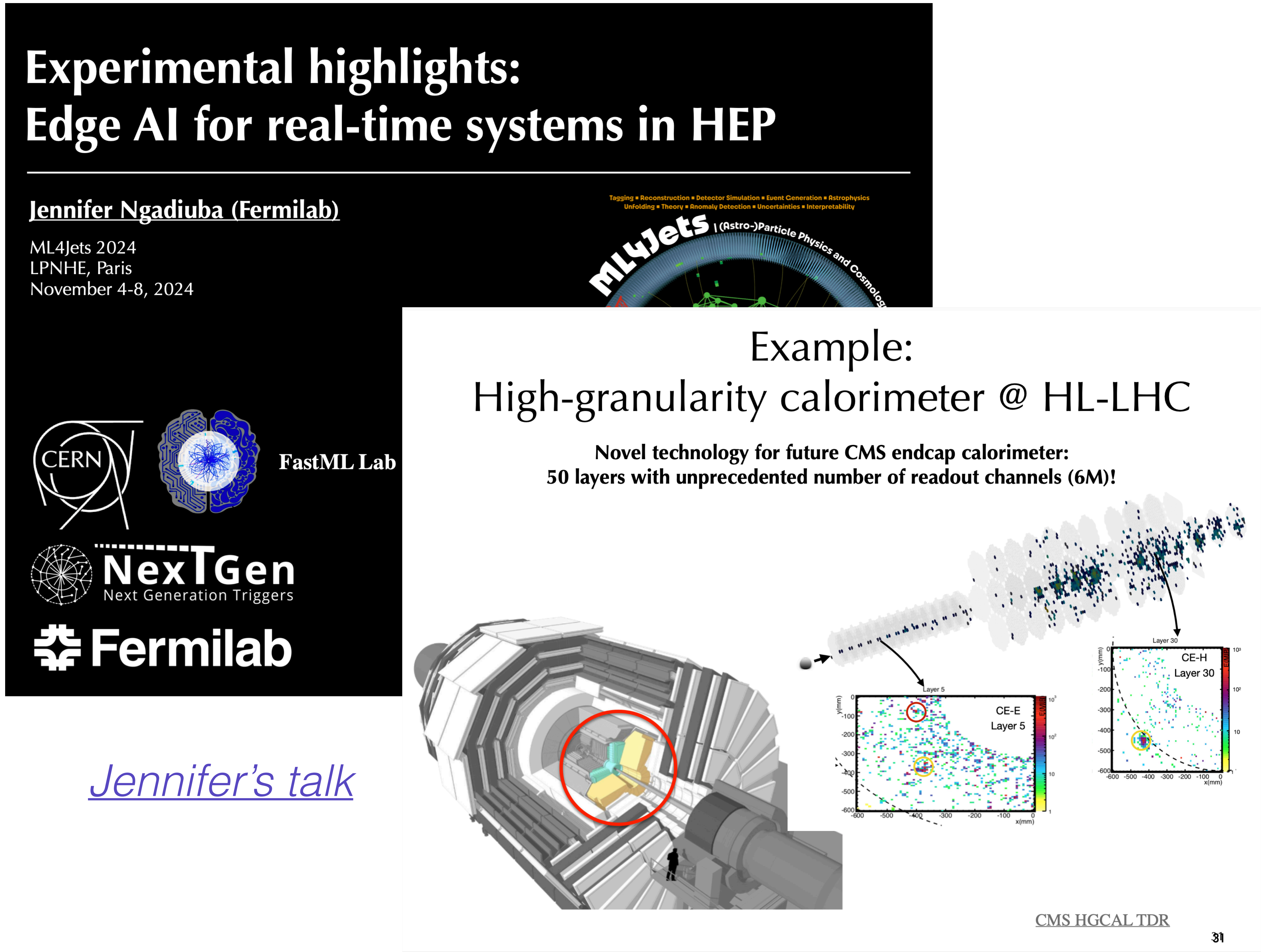


מכון ויצמן למדע
WEIZMANN INSTITUTE OF SCIENCE

Nilotpal Kakati, *Etienne Dreyer, Eilam Gross*

(nilotpal.kakati@cern.ch)

Last Monday,



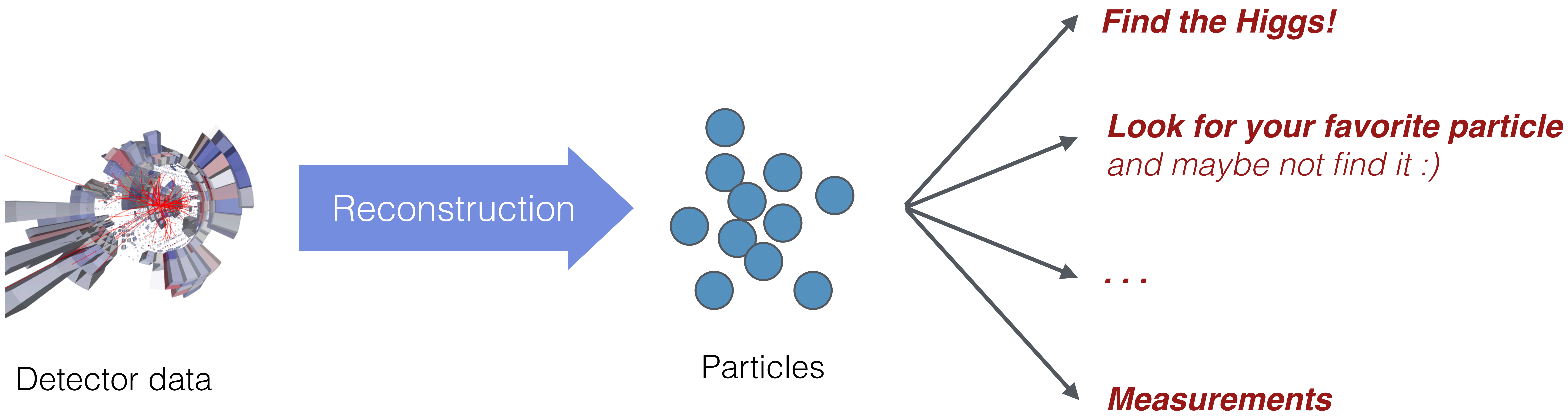
[Jennifer's talk]

… What if we try to upscale calorimeters with AI?

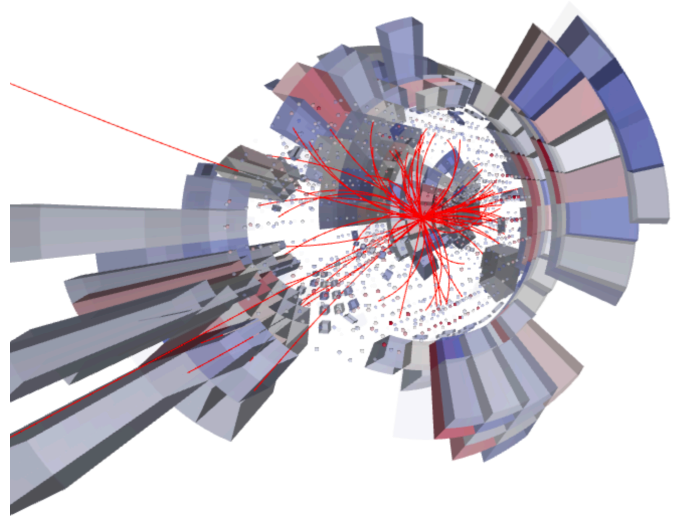
(shameless self self-plugin from the audience): Ah we tried that exact thing, and will talk about it on Wednesday…

This is the talk!

Why need (better) detectors?

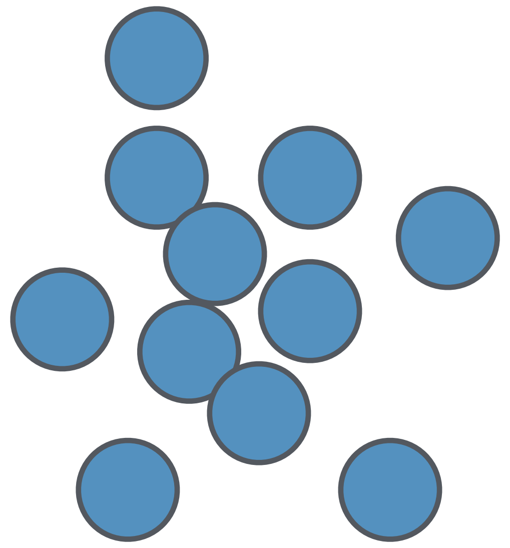


Why need (better) detectors?



Detector data

Reconstruction



Particles

Find the Higgs!

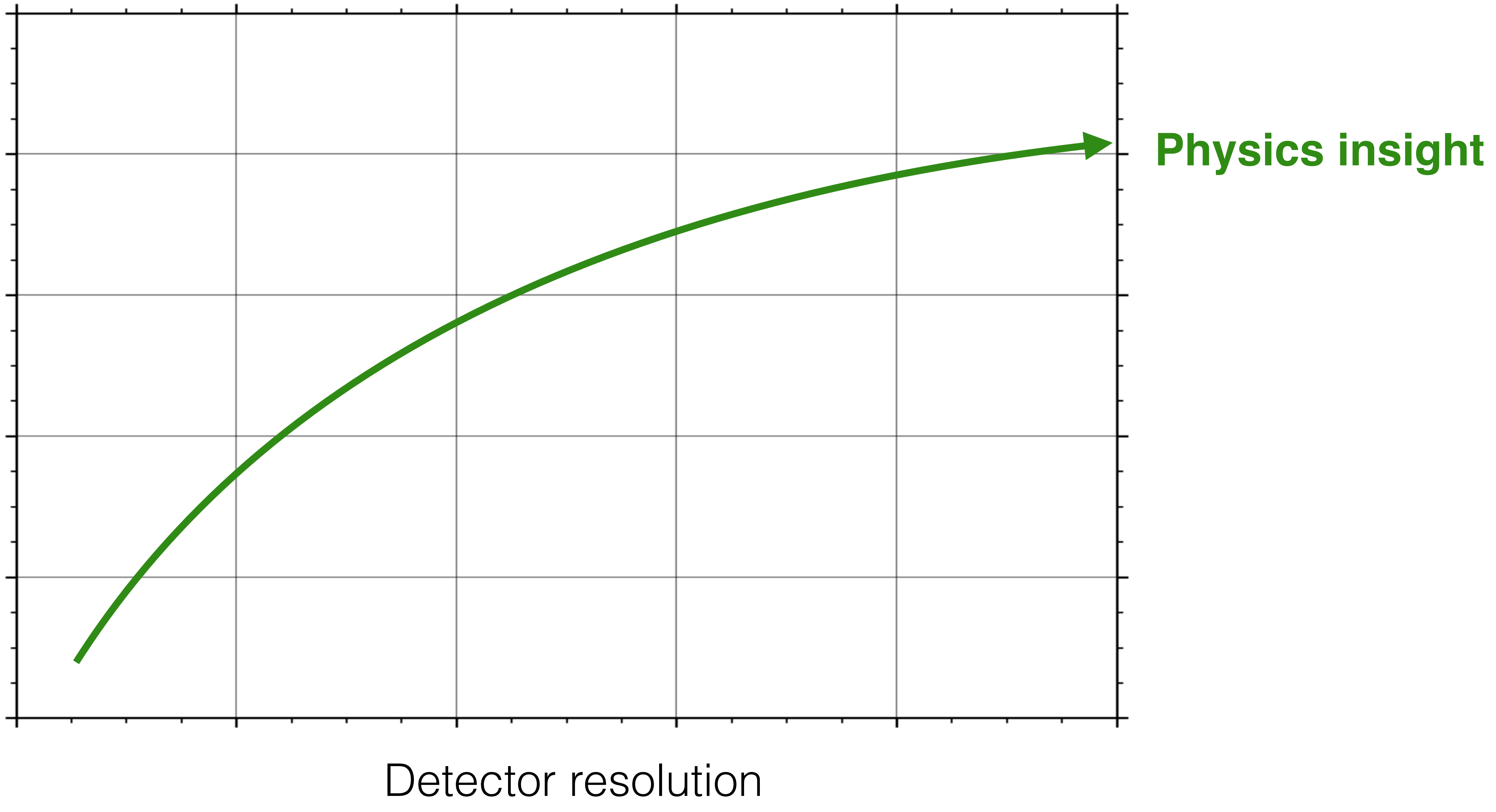
Look for your favorite particle
and maybe not find it :)

. . .

Measurements

Better detector resolution → Better particle reconstruction → Better physics result

But, no free lunch…



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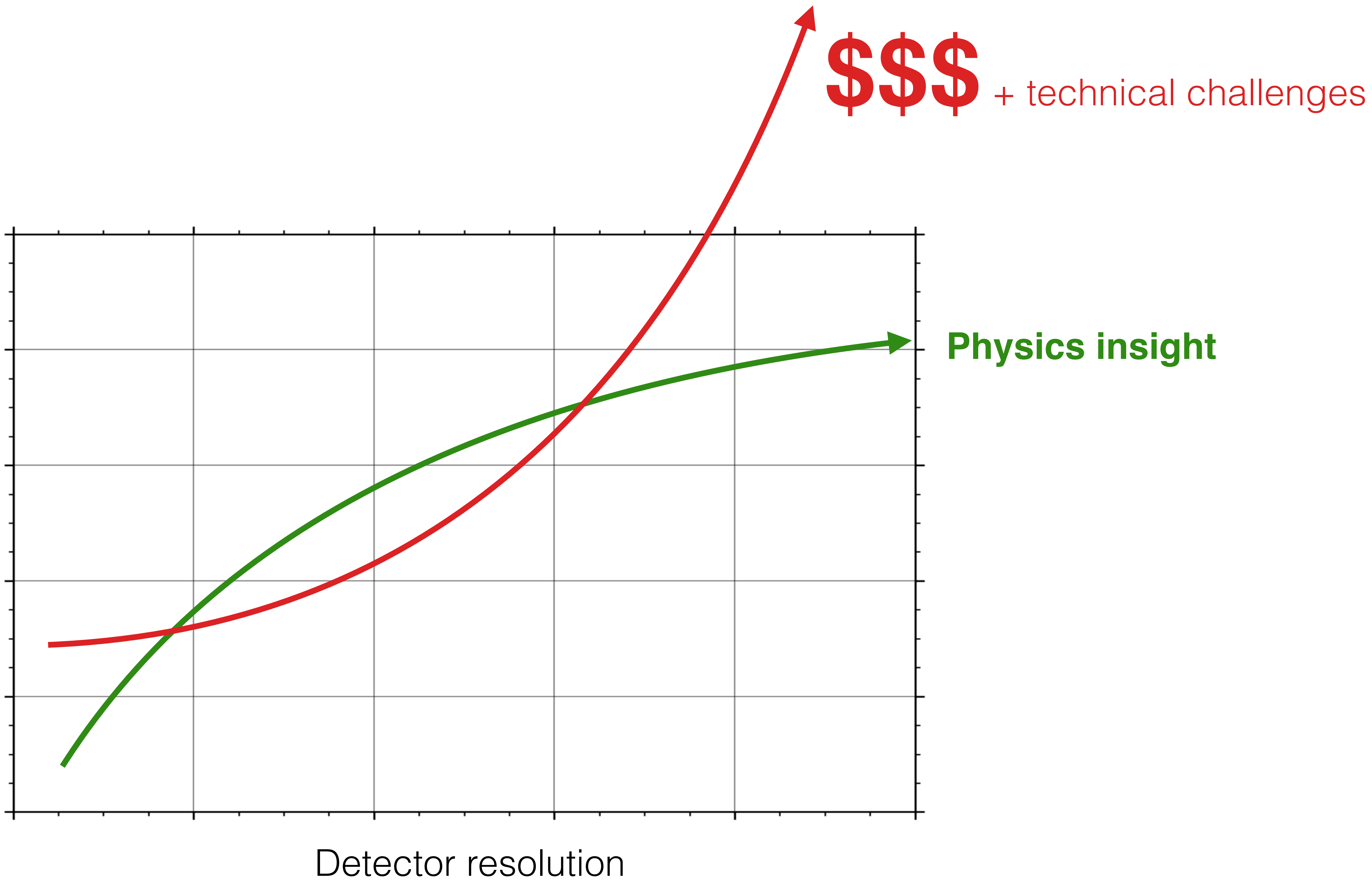
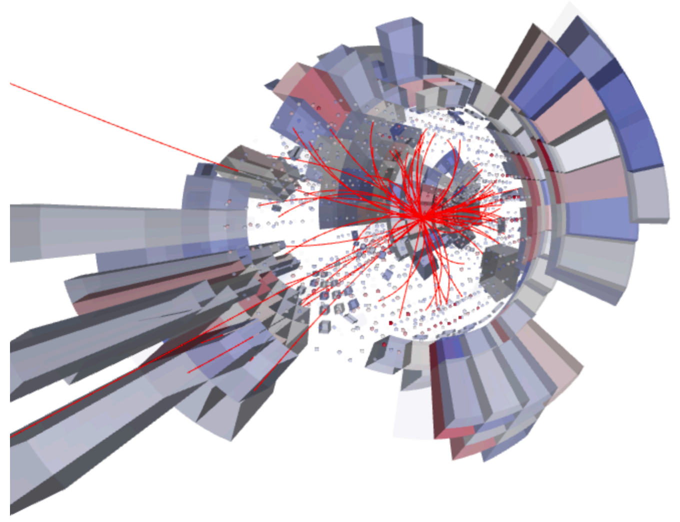
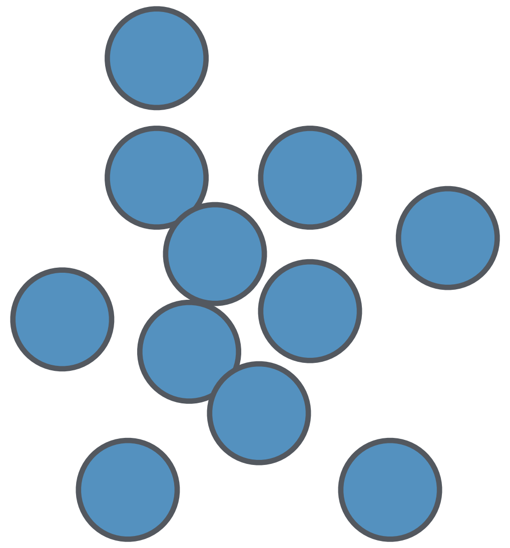


Let’s ask



Detector data

Reconstruction



Particles

Find the Higgs!

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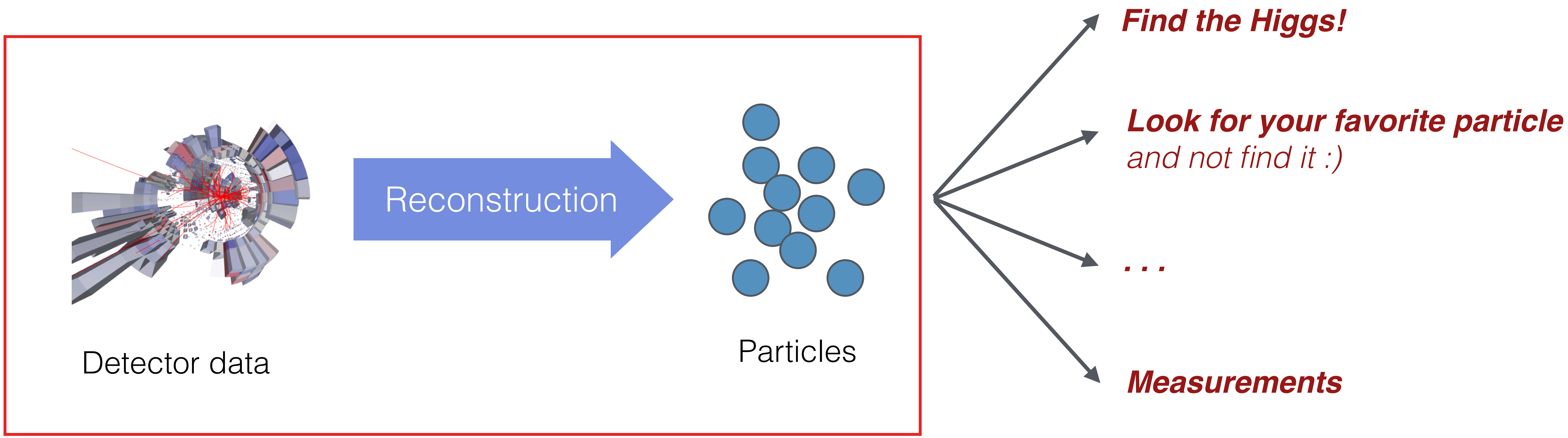
...

Measurements

AI super resolution magic
to the rescue??

Let’s ask

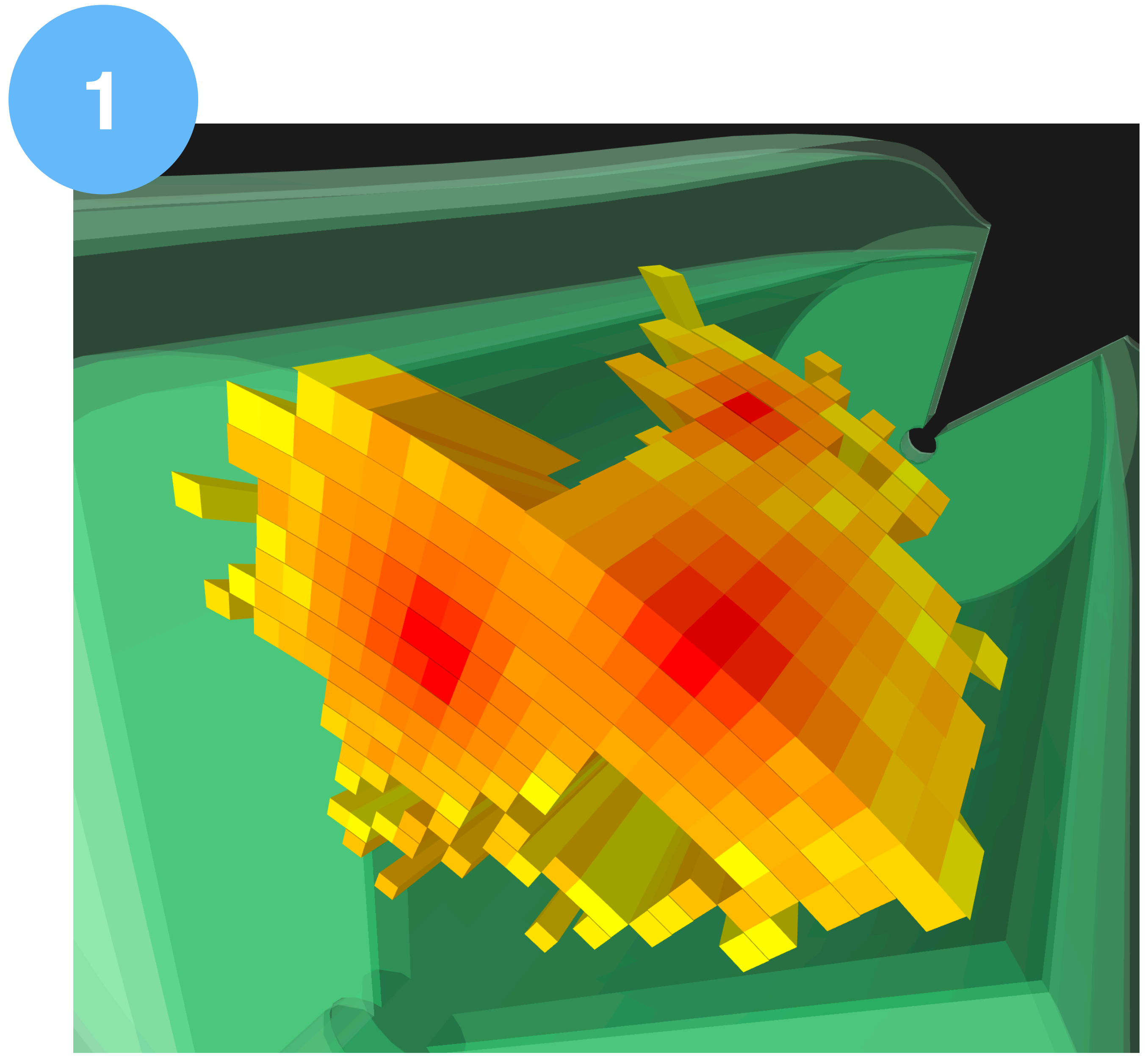


AI super resolution magic
to the rescue??

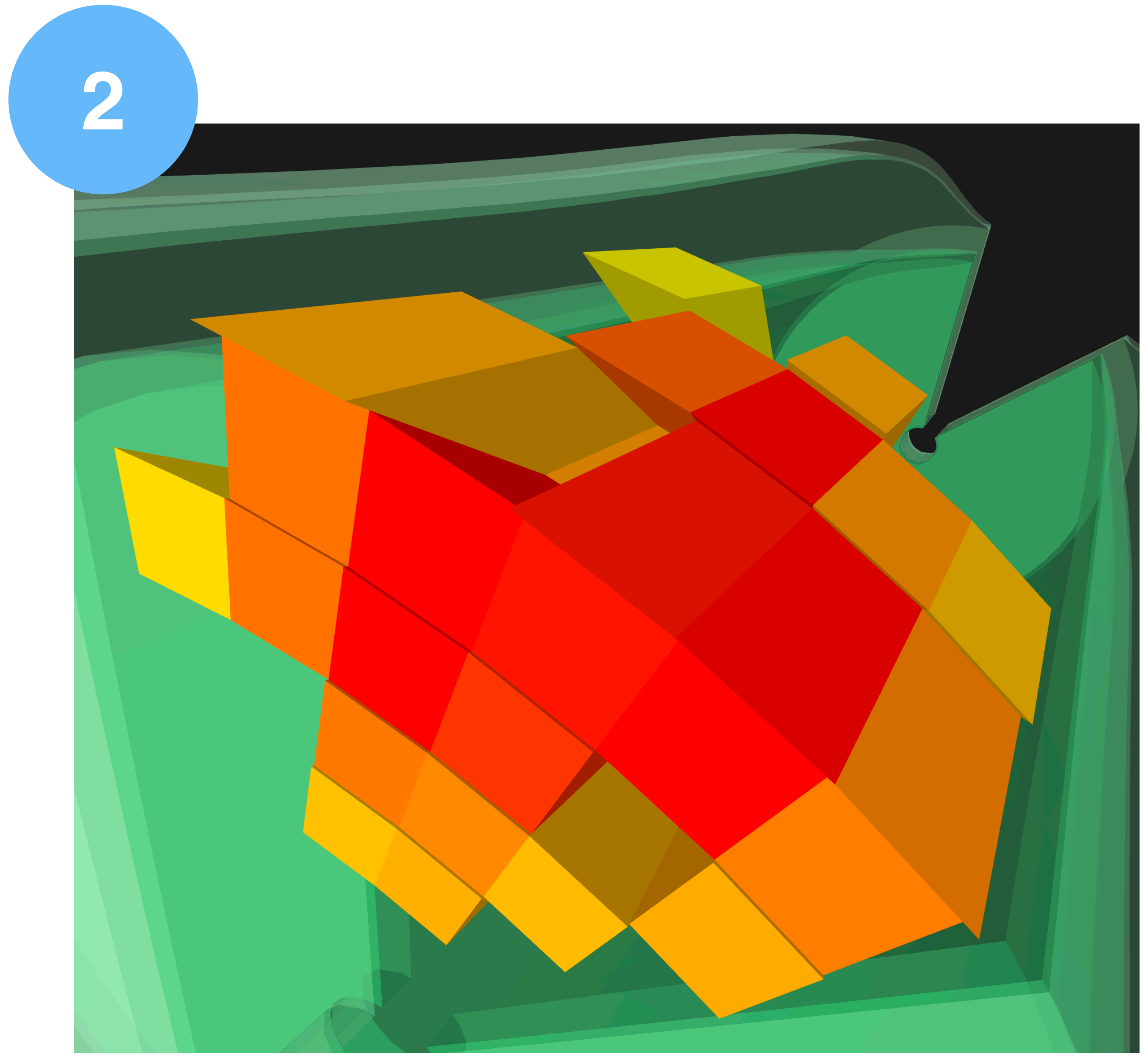
Let’s get a bit technical…

Data Generation Setup

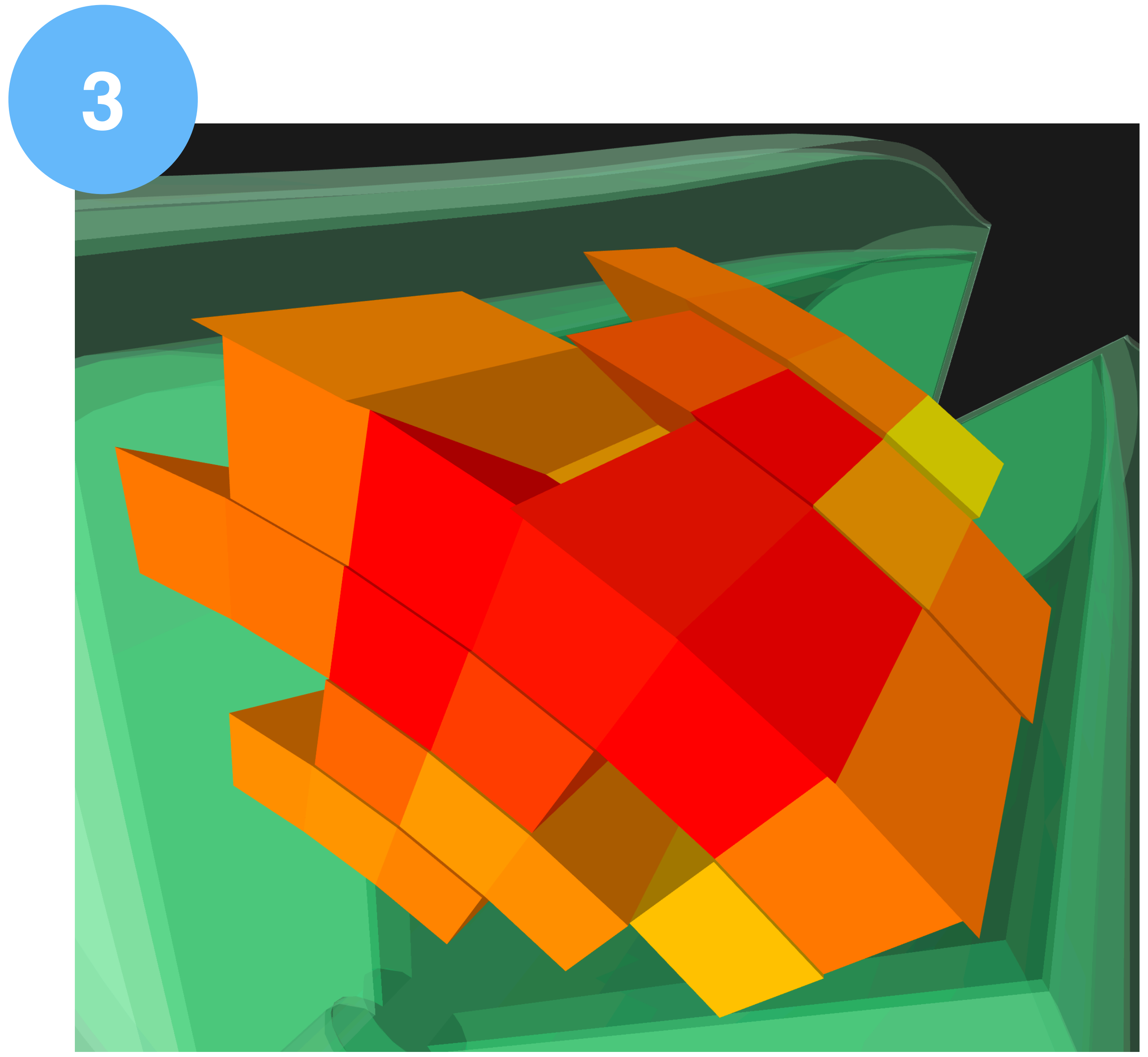
- COCOA mod (https://iopscience.iop.org/article/10.1088/2632-2153/acf186/pdf)



High Resolution
(No noise)

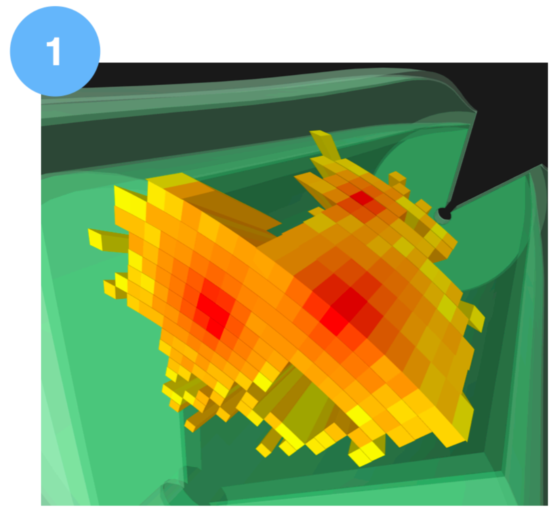


Low Resolution
(Sum up cells in η, ϕ)

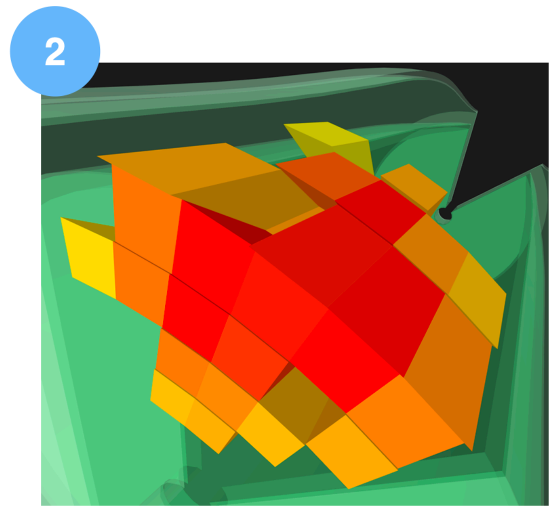


Add noise

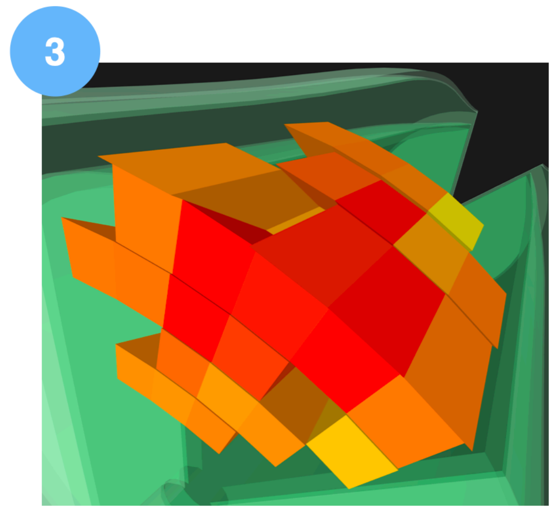
ML Goal



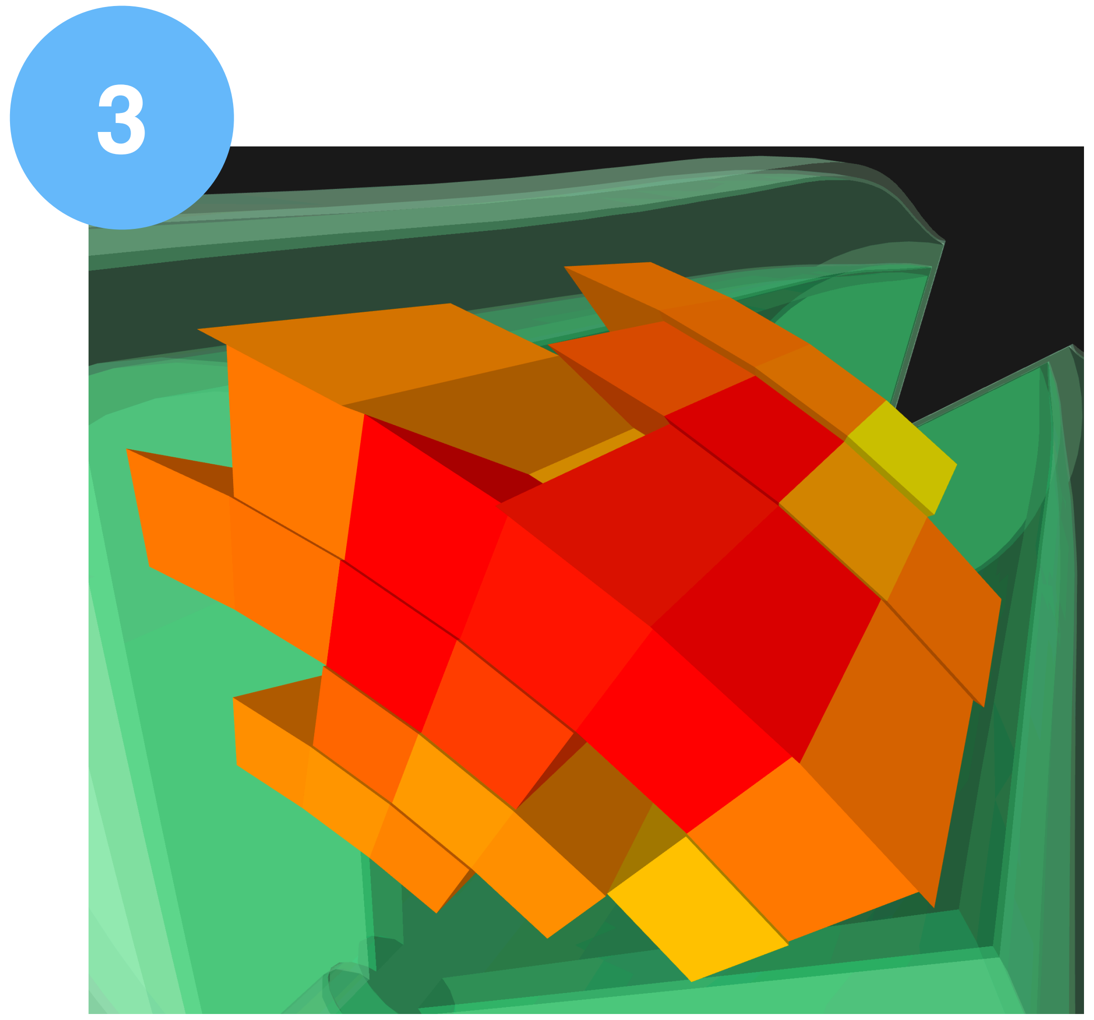
High Resolution



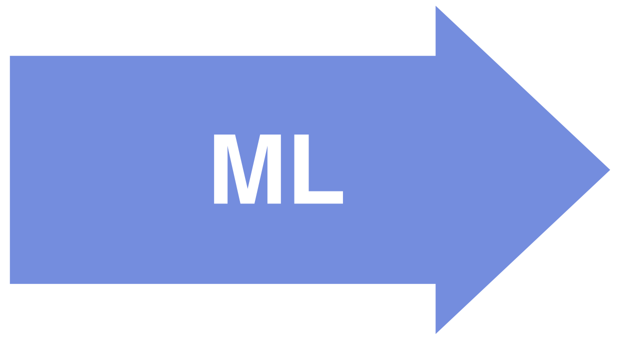
Low Resolution
(Sum up cells)

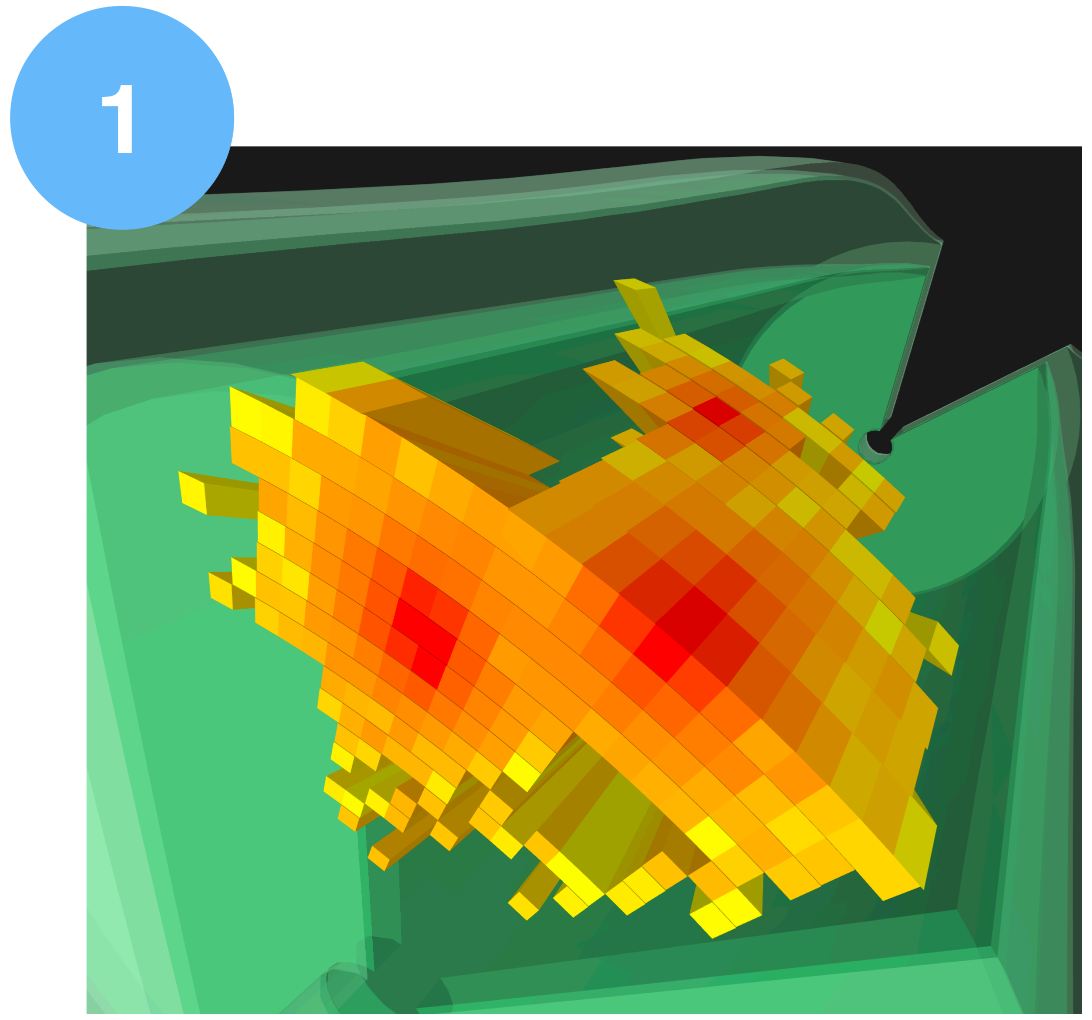


Add noise



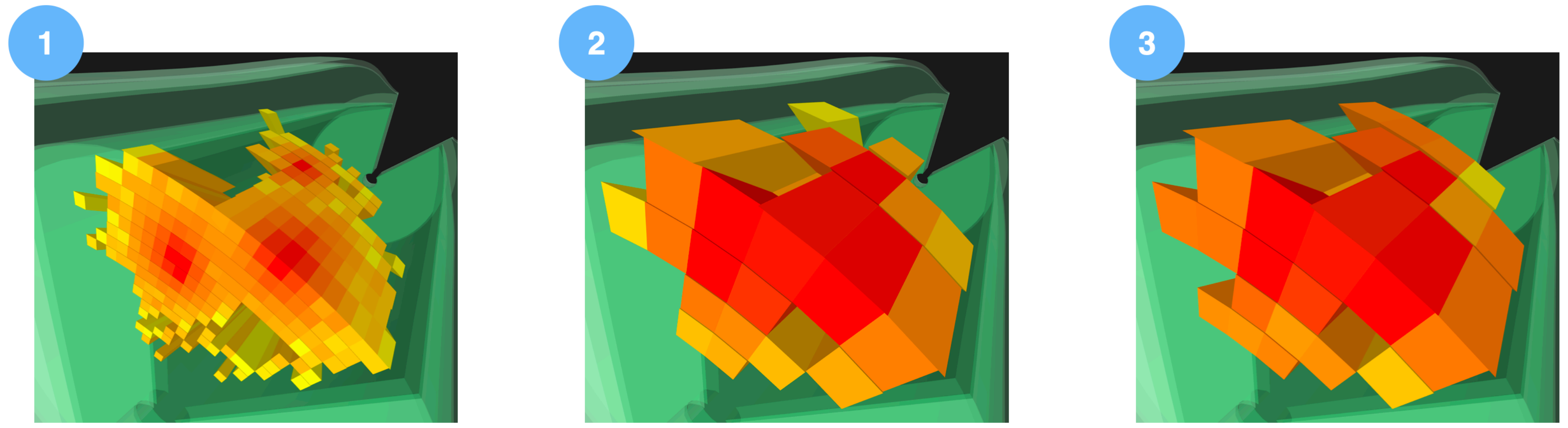
Low Resolution + noise





High Resolution + no noise

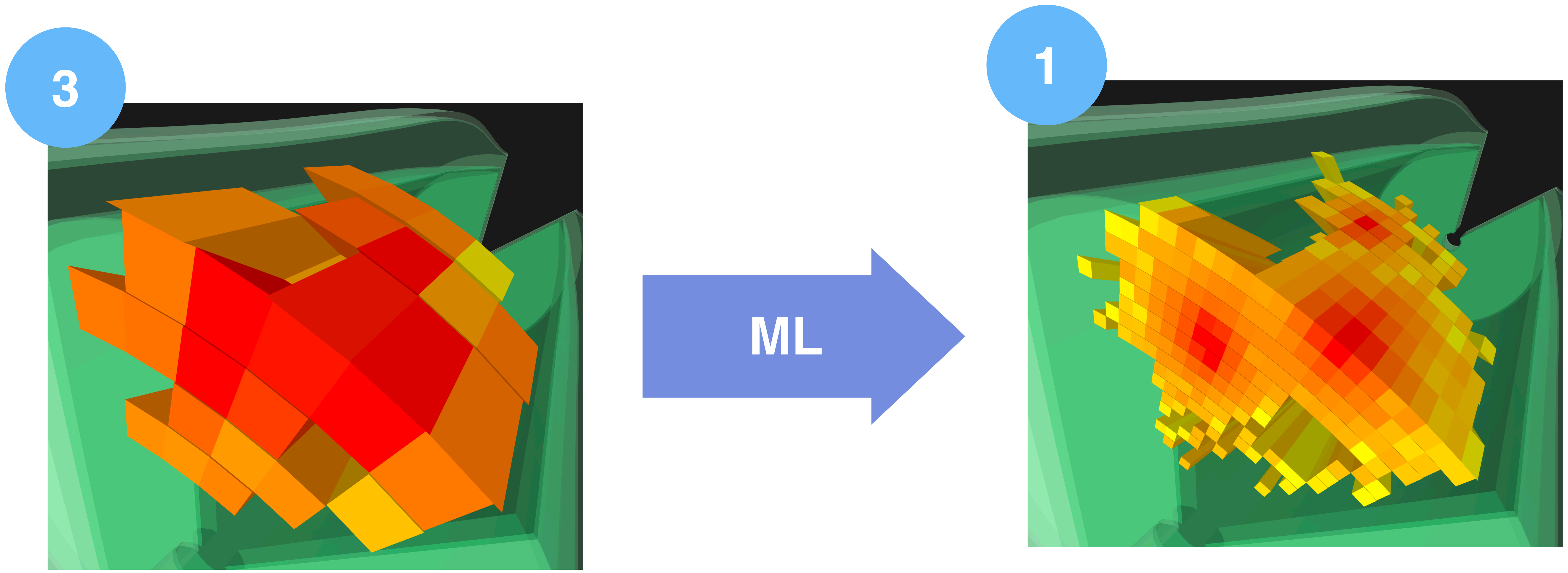
ML Goal



High Resolution

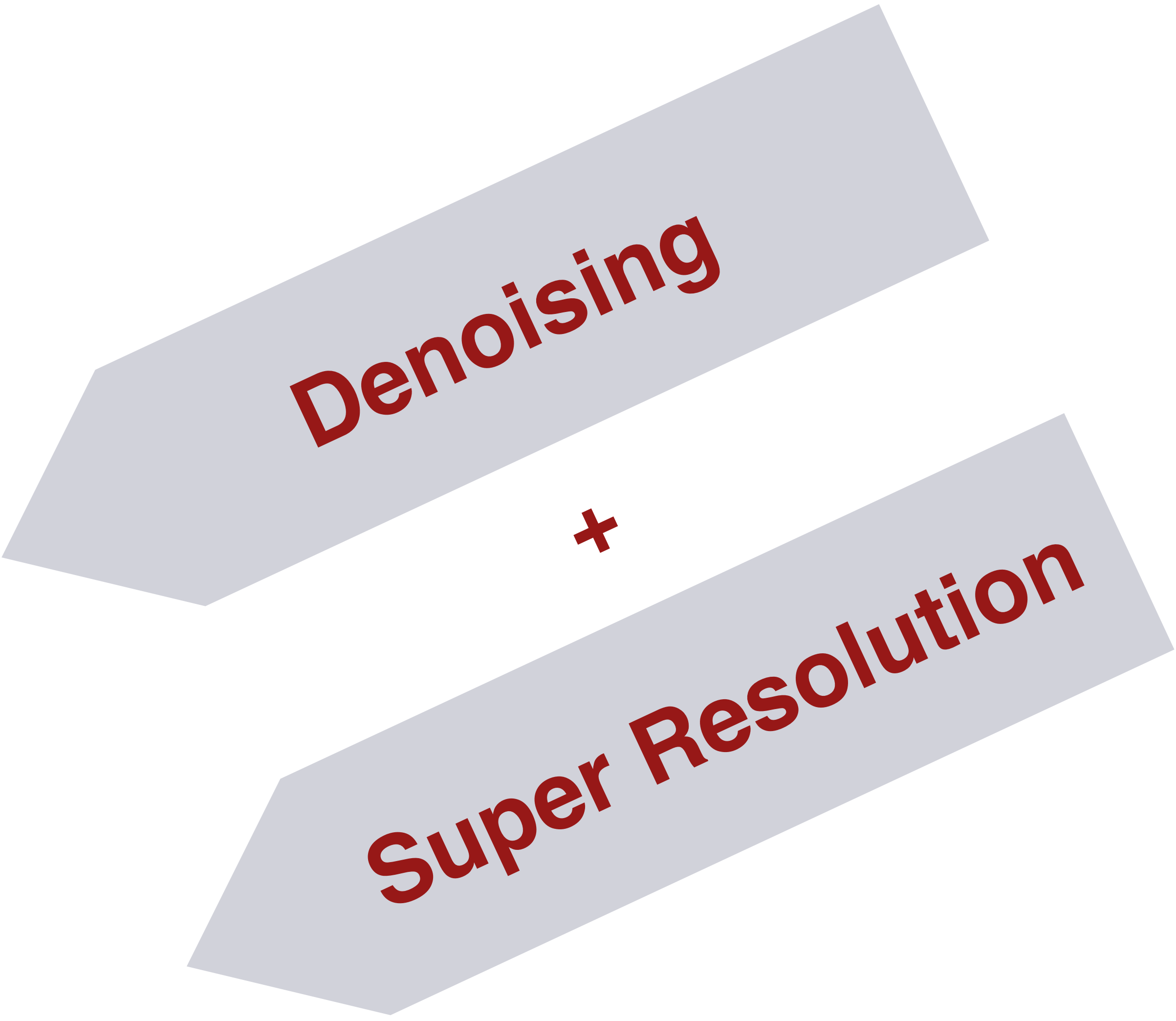
Low Resolution
(Sum up cells)

Add noise



Low Resolution + noise

High Resolution + no noise



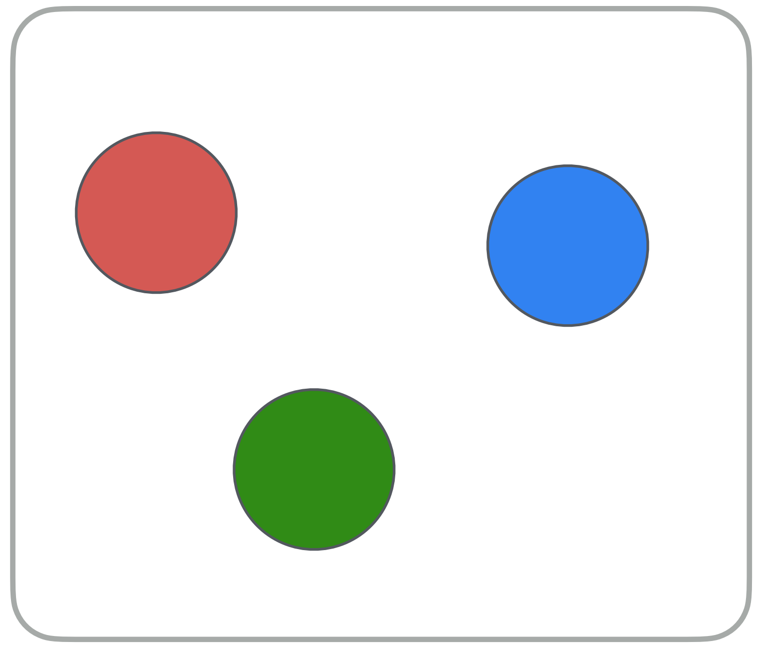
ML set up

- Inspired by the SR3 paper

Image Super-Resolution via Iterative Refinement (https://arxiv.org/pdf/2104.07636.pdf)

- Images → Graph
- Diffusion → Flow Matching
- Fancier network architecture

ML set up



Low Res Graph

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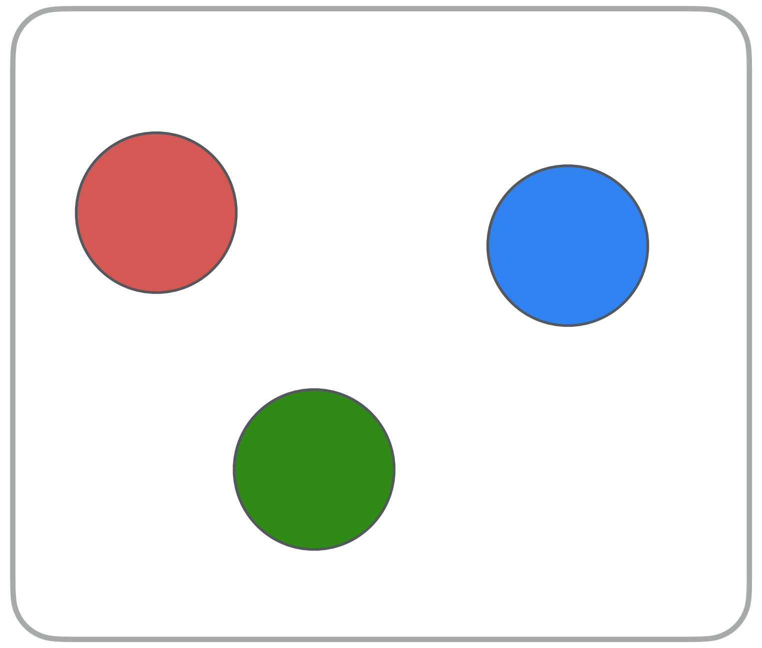
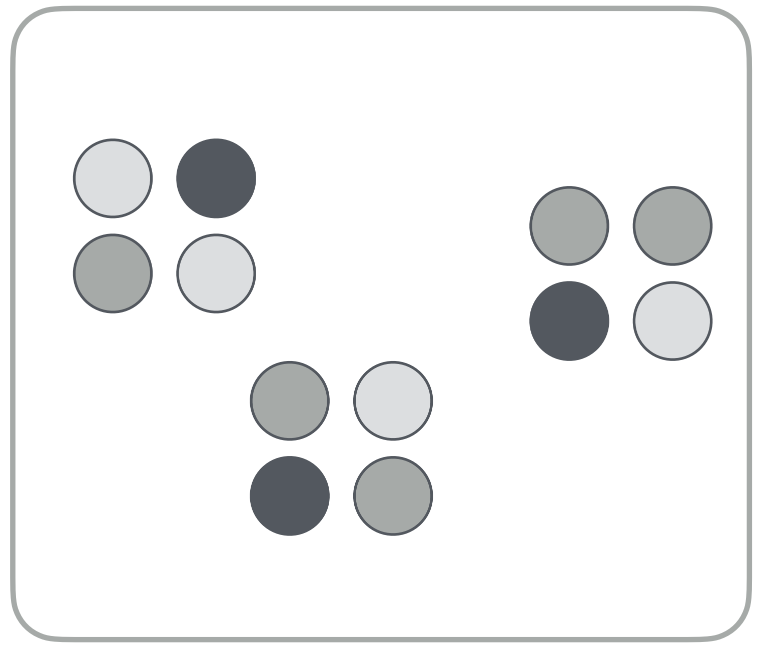


Low Res Graph



$\mathcal{N}(0,I)$

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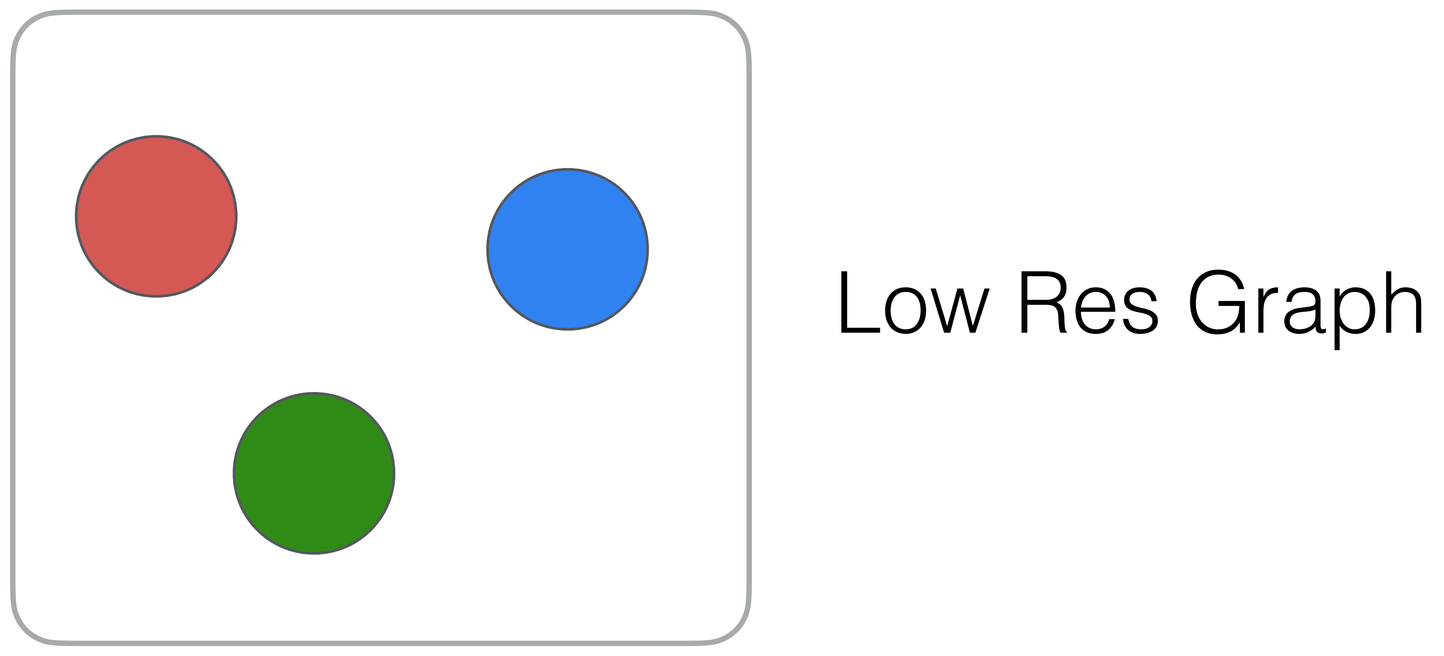

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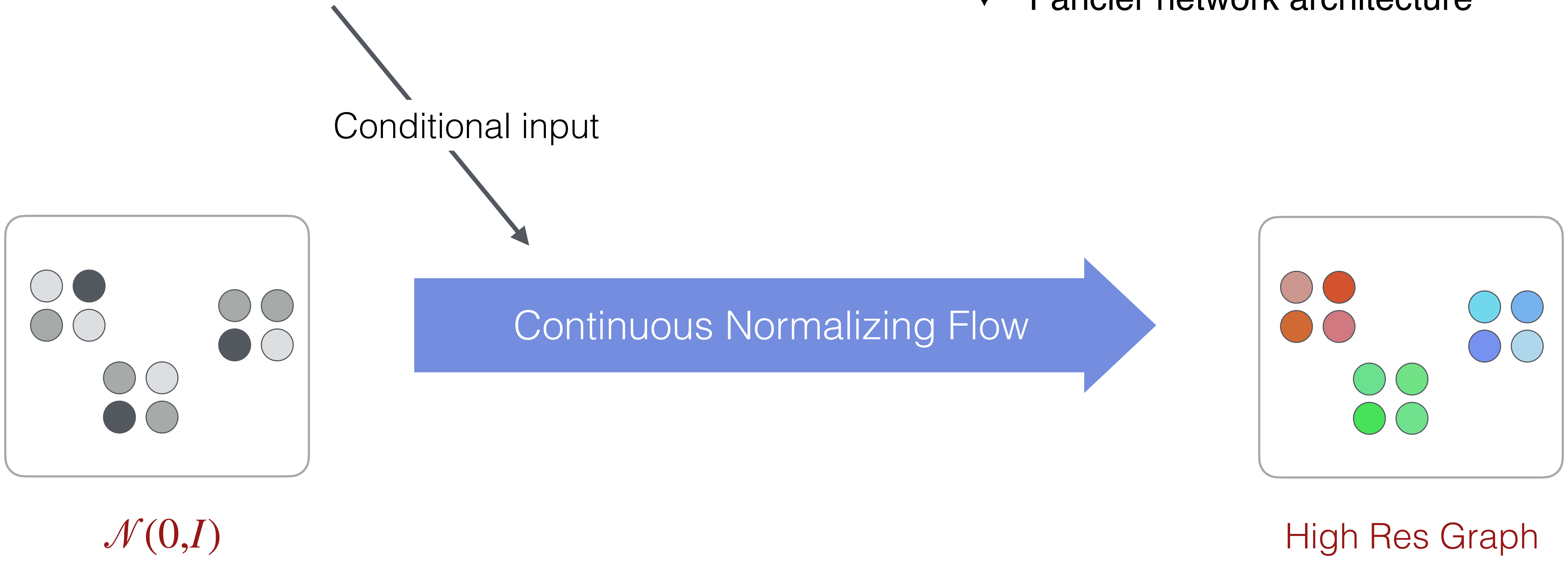
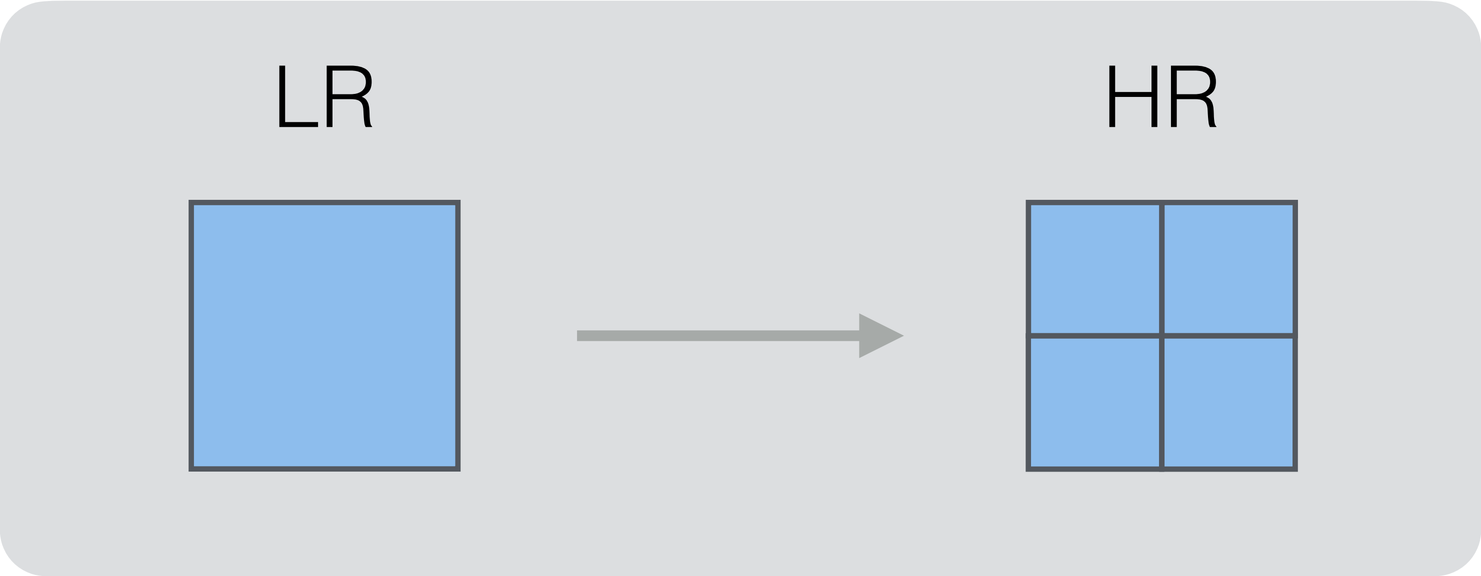


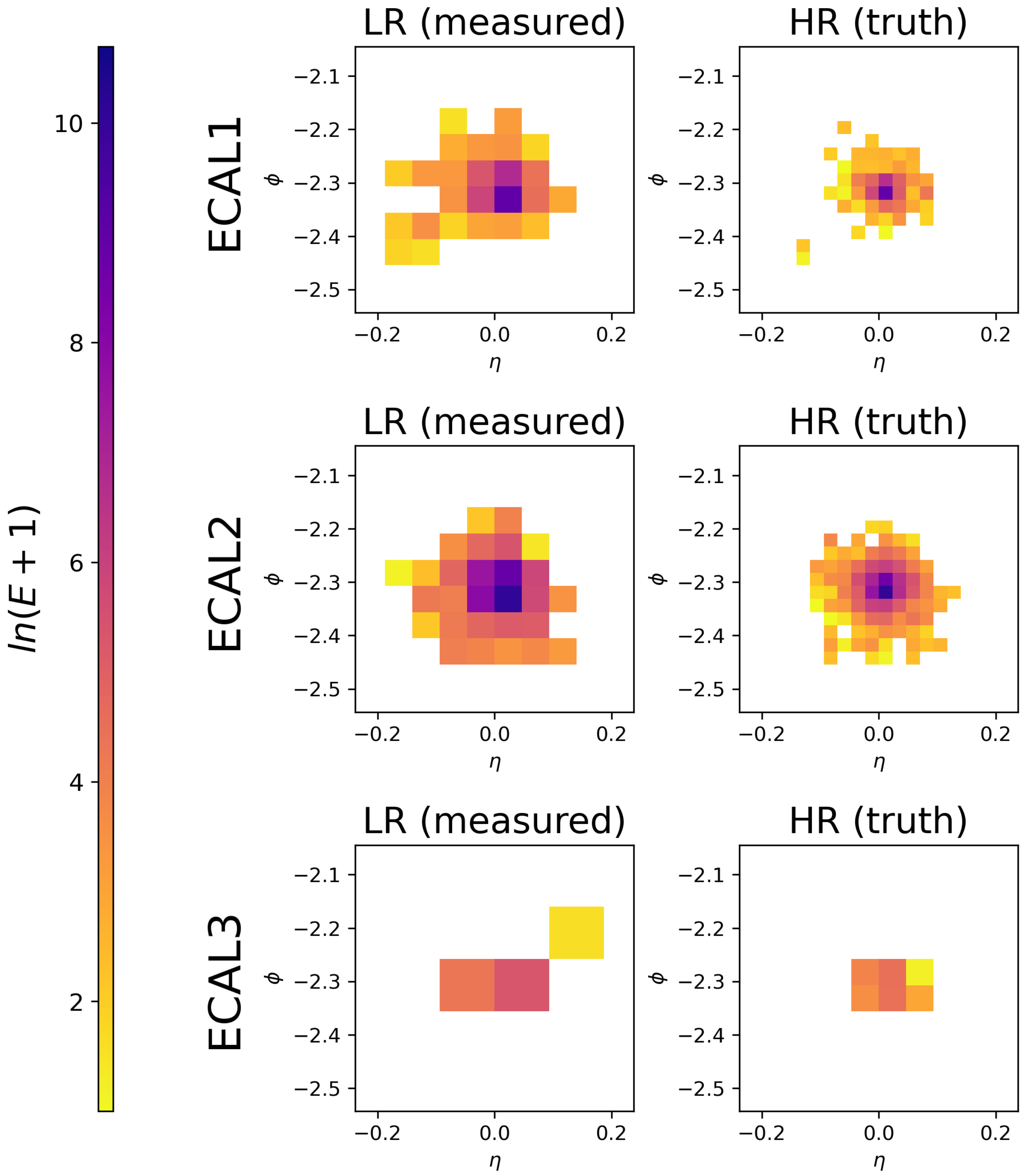
(Baby) step 1: Single electron

Simplest case

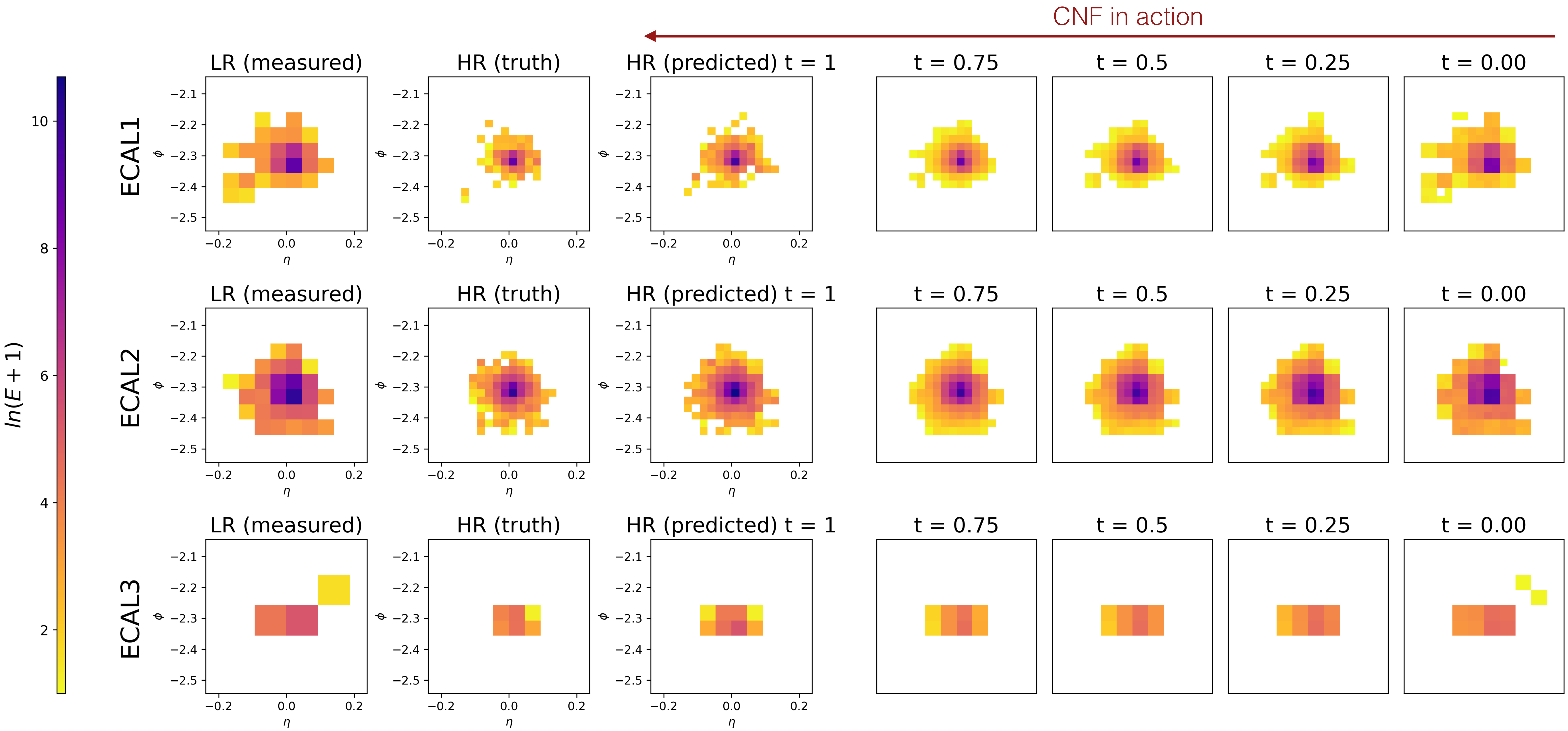


- Electron gun (one event = one electron)
  - ➡ $p_T \in [50, 51]\ GeV$
  - ➡ $\eta \in [-0.01, 0.01] \quad \phi \in [-\pi, \pi)$
- $2x \times 2x = 4x$ upscaling

Event display *(graphs as images)*

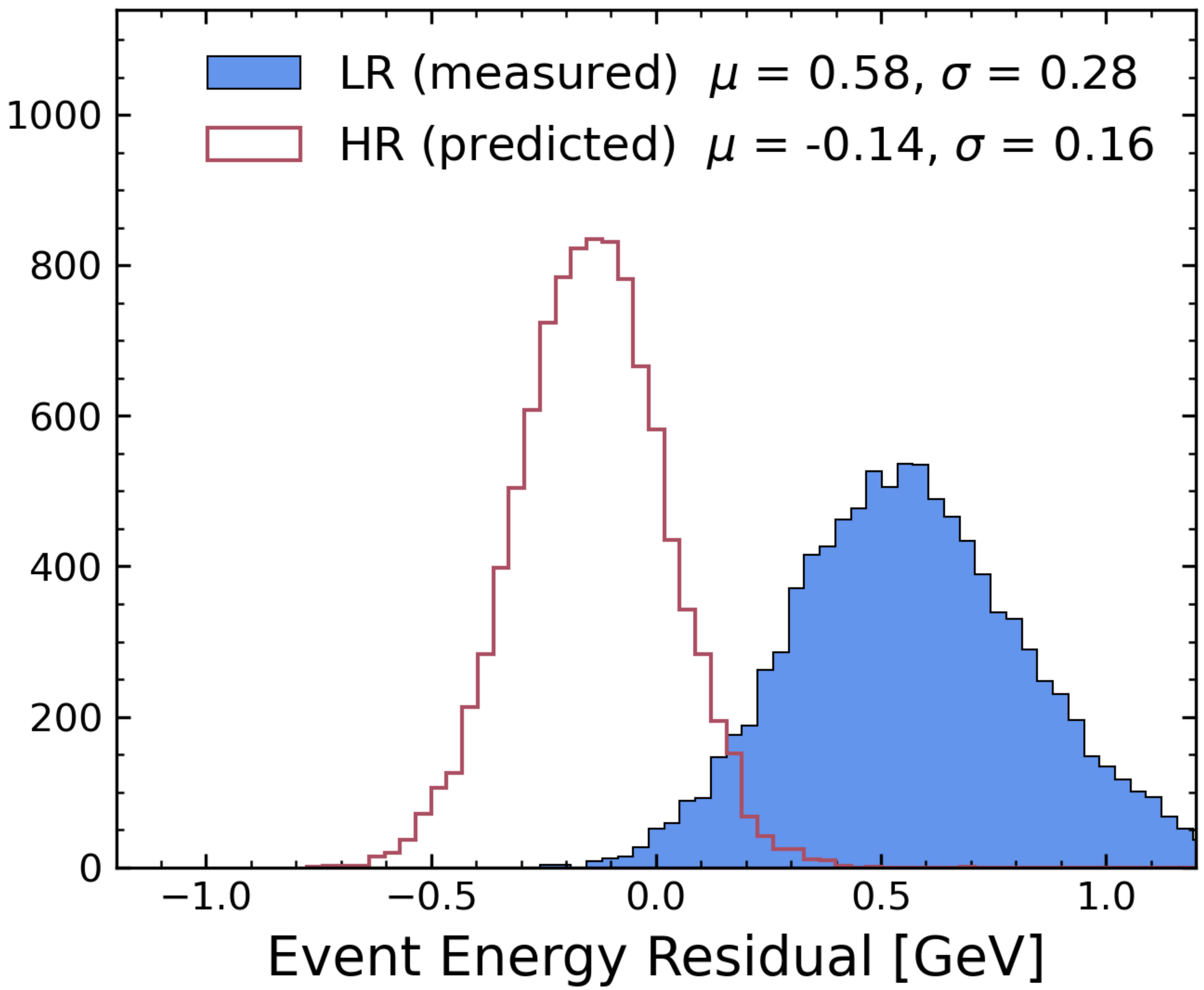


Event display *(graphs as images)*

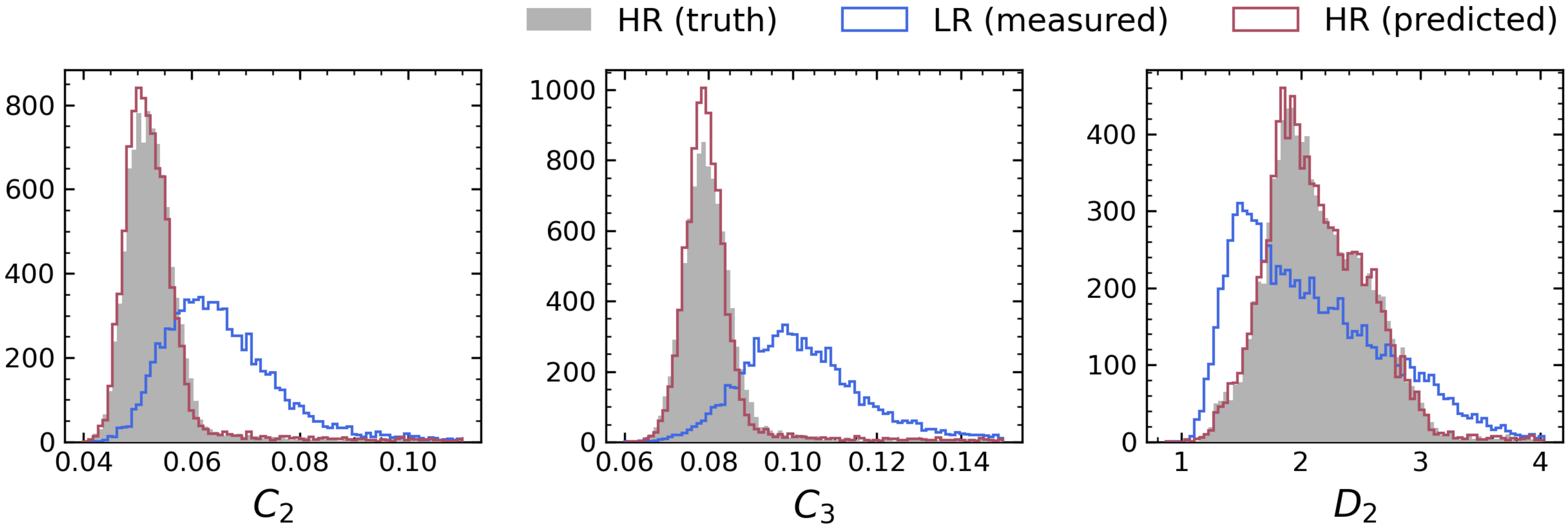


Quantitatively

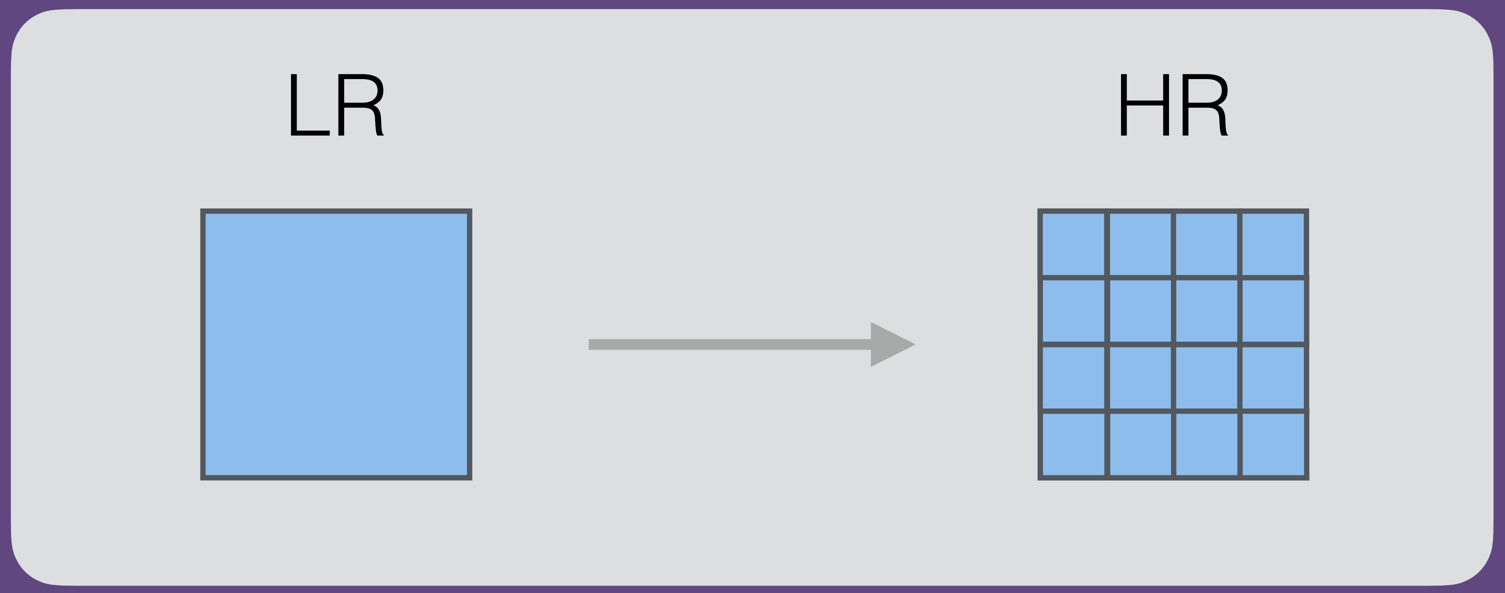
- Event energy = electron energy
- Shift in LR is because we were not storing negative energy cells.
  - Network manages to fix it



Substructure

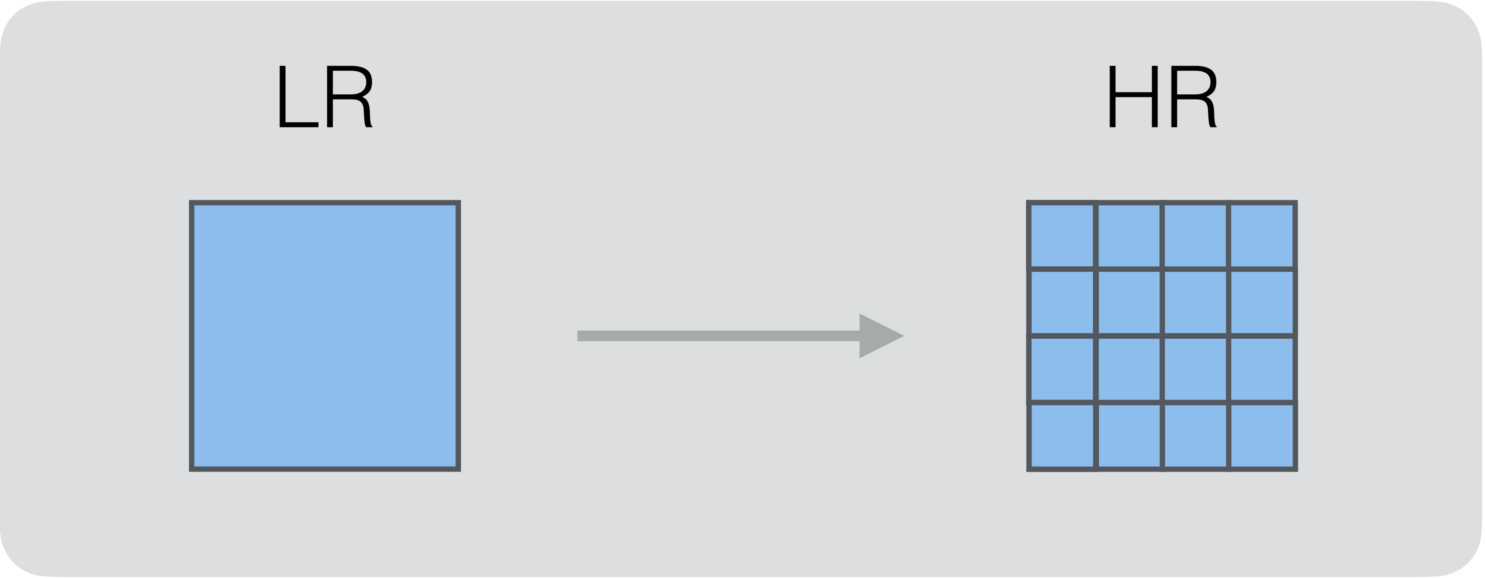


A more interesting case - *more particles, more upscaling…*



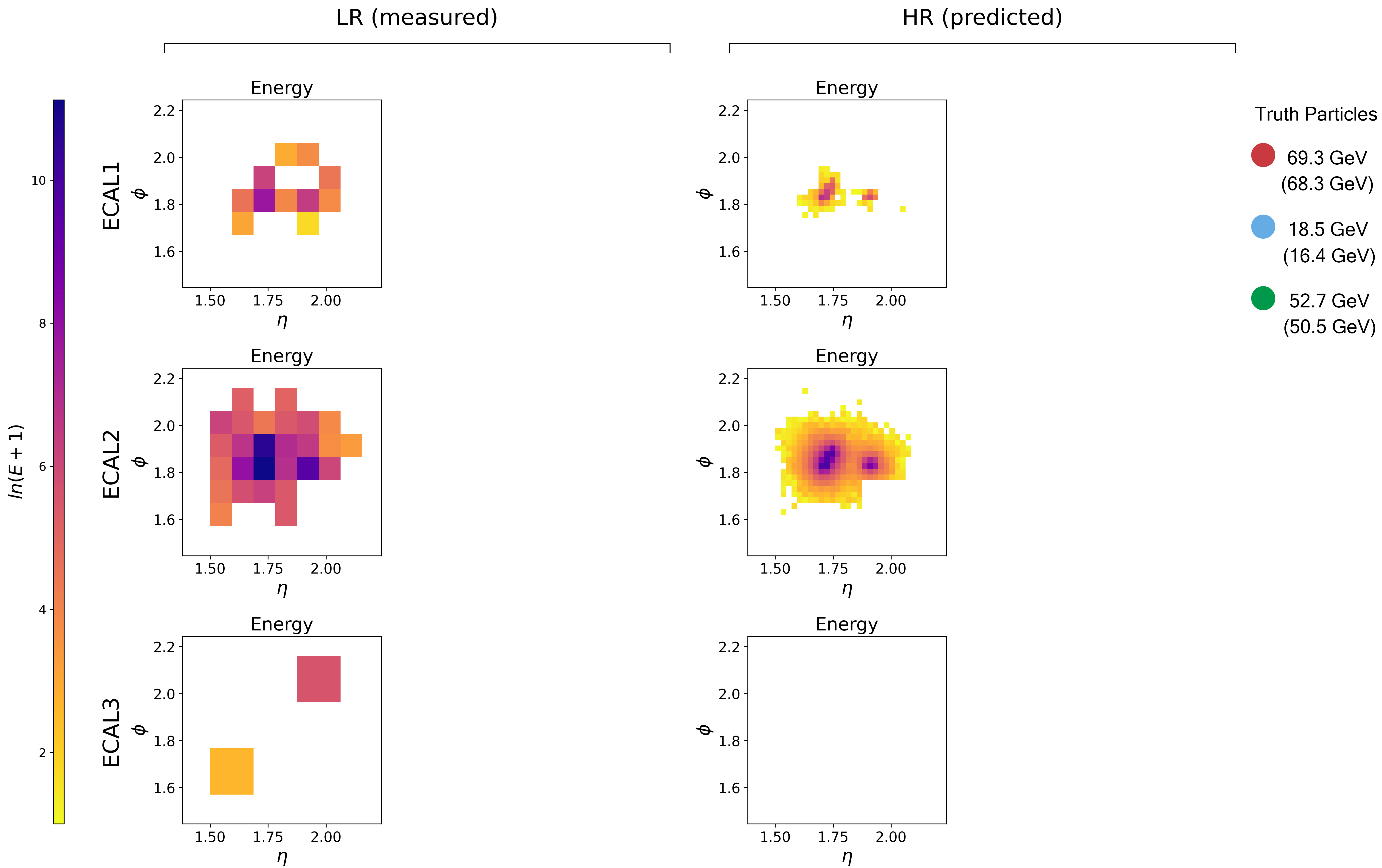
A more Interesting case!

- Multiple particles
  - Single electron with
    - $p_T \in [20,50]\ GeV$
    - $\eta \in [-2.5,2.5] \quad \phi \in [-\pi, \pi)$
  - Closely accompanied by 0-3 photons with $p_T \in [5,25]\ GeV$

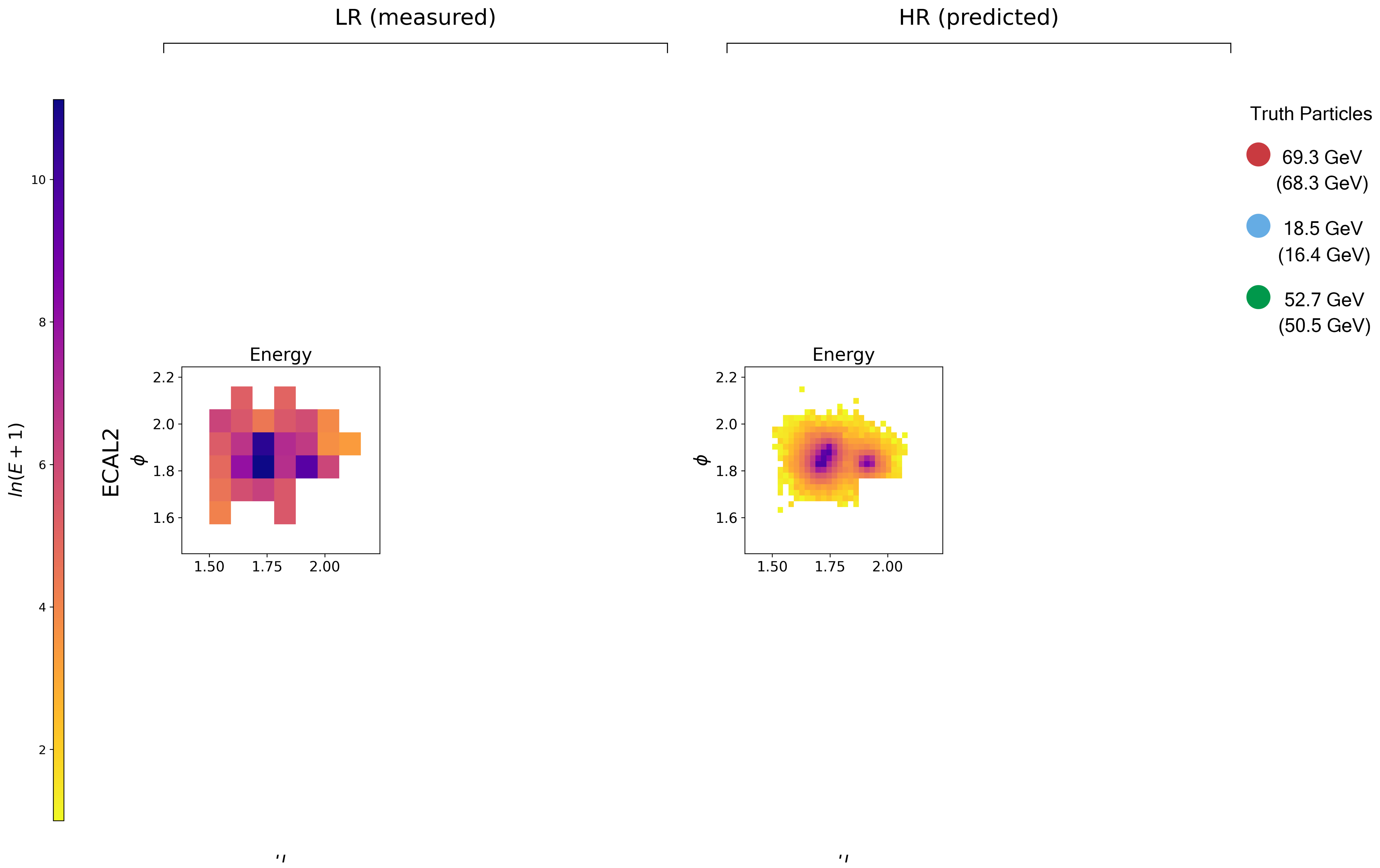


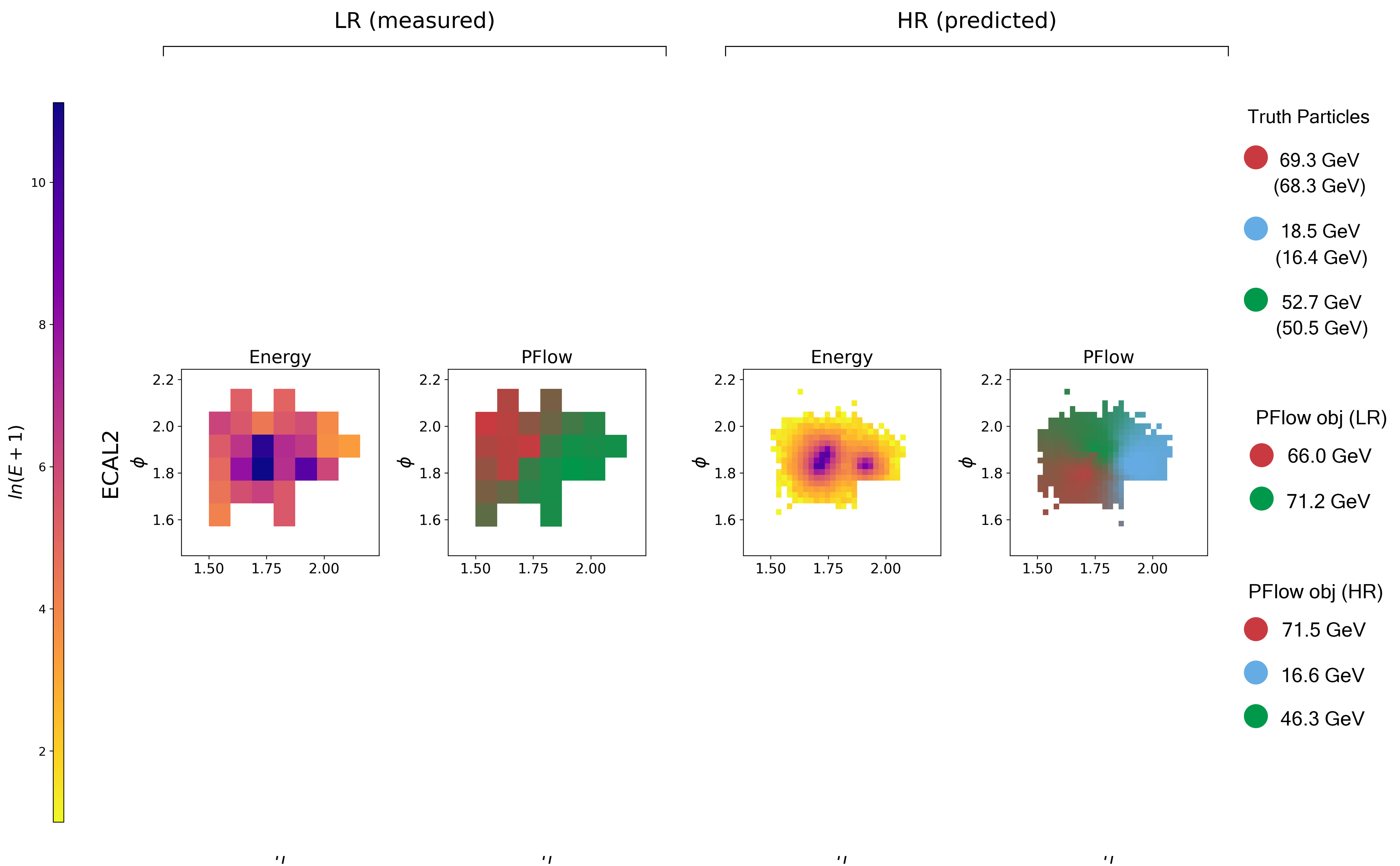
$4x \times 4x = 16x$ upscaling

- Train identical reconstruction algorithm with identical hyper parameters on the low-res and high-res data, and look at reconstruction performance
  - *Novel reconstruction algorithm (skipping, sorry!)*
  - Predicts fractional association of each cell to particles (cross attention!)



LR (measured)
HR (predicted)
Energy
ECAL1
ECAL2
ECAL3
ϕ
η
$ln(E+1)$
Truth Particles
69.3 GeV
(68.3 GeV)
18.5 GeV
(16.4 GeV)
52.7 GeV
(50.5 GeV)

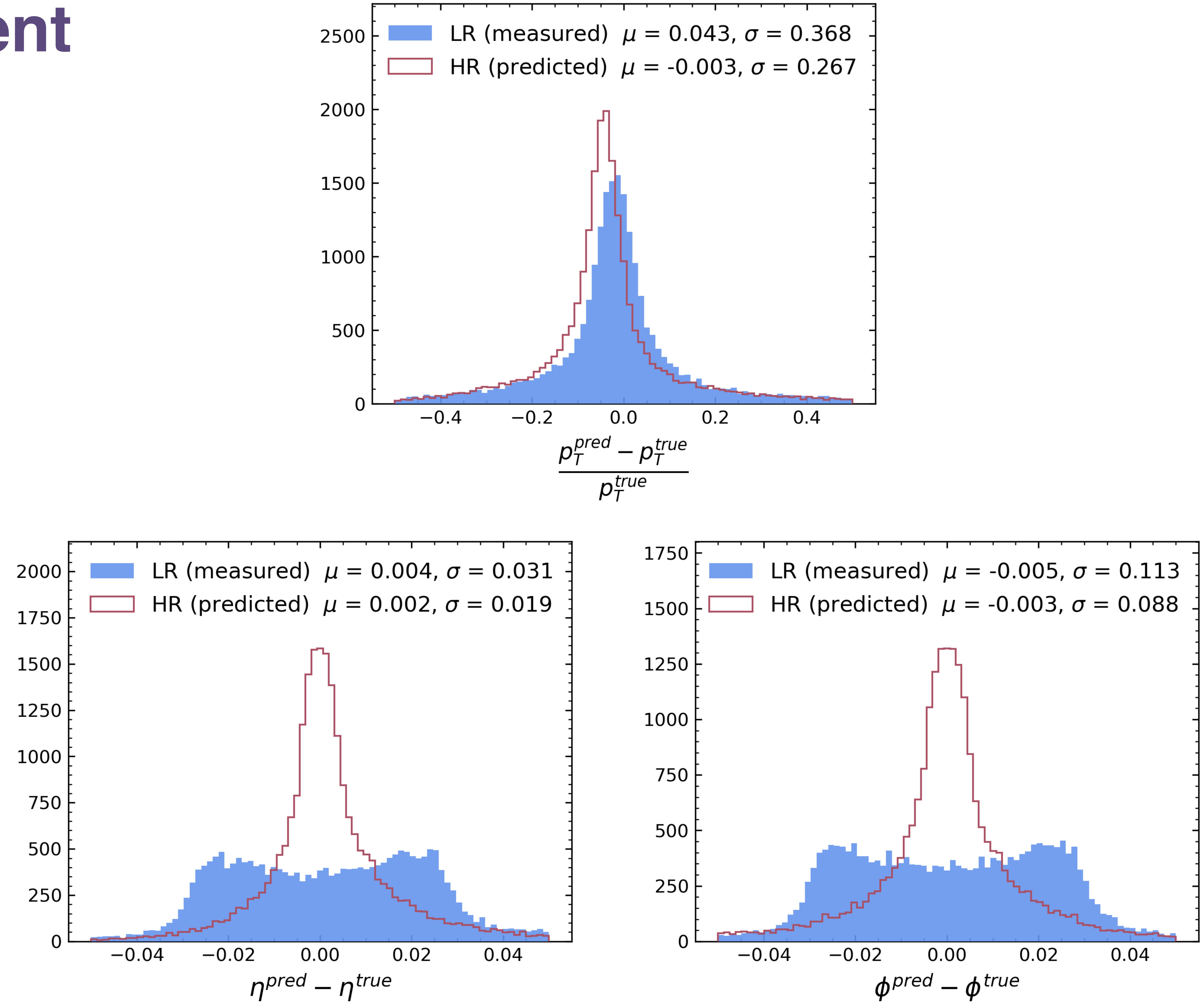

LR (measured)
HR (predicted)
ln(E + 1)
ECAL2
Energy
ϕ
2.2
2.0
1.8
1.6
1.50
1.75
2.00
Truth Particles
69.3 GeV
(68.3 GeV)
18.5 GeV
(16.4 GeV)
52.7 GeV
(50.5 GeV)



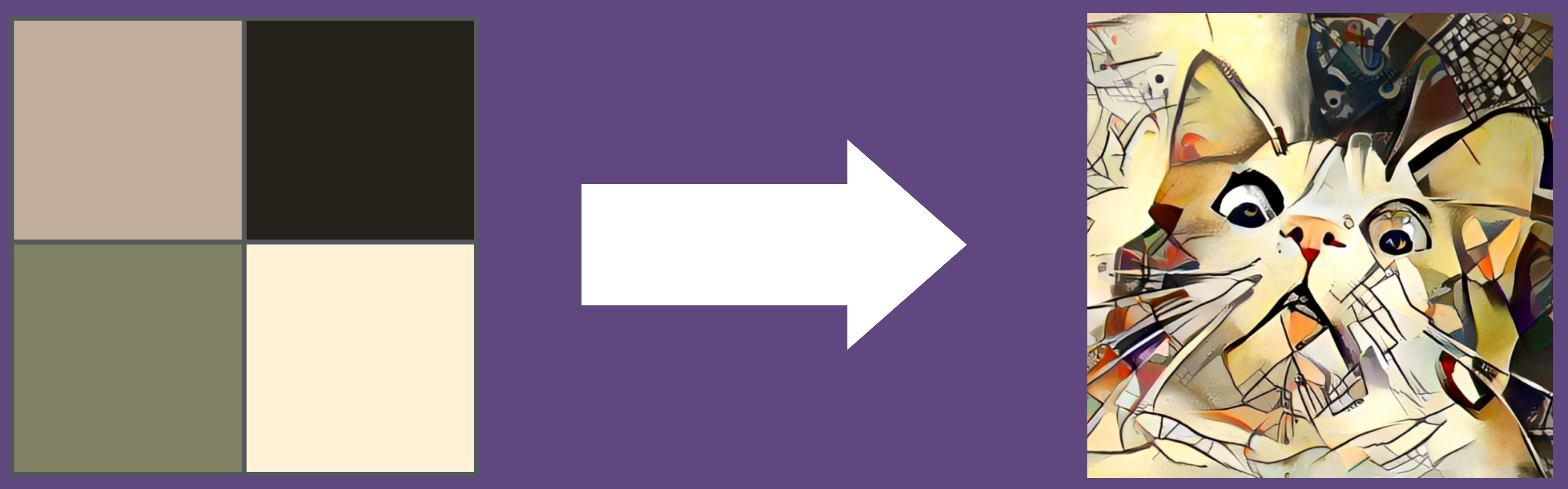
LR (measured)
HR (predicted)
ln(E + 1)
ECAL2
Energy
PFlow
Energy
PFlow
ϕ
Truth Particles
69.3 GeV
(68.3 GeV)
18.5 GeV
(16.4 GeV)
52.7 GeV
(50.5 GeV)
PFlow obj (LR)
66.0 GeV
71.2 GeV
PFlow obj (HR)
71.5 GeV
16.6 GeV
46.3 GeV

Quantitative improvement

- Improved p_T resolution
  - Denoising
- Improved η, ϕ resolution
  - Super resolution



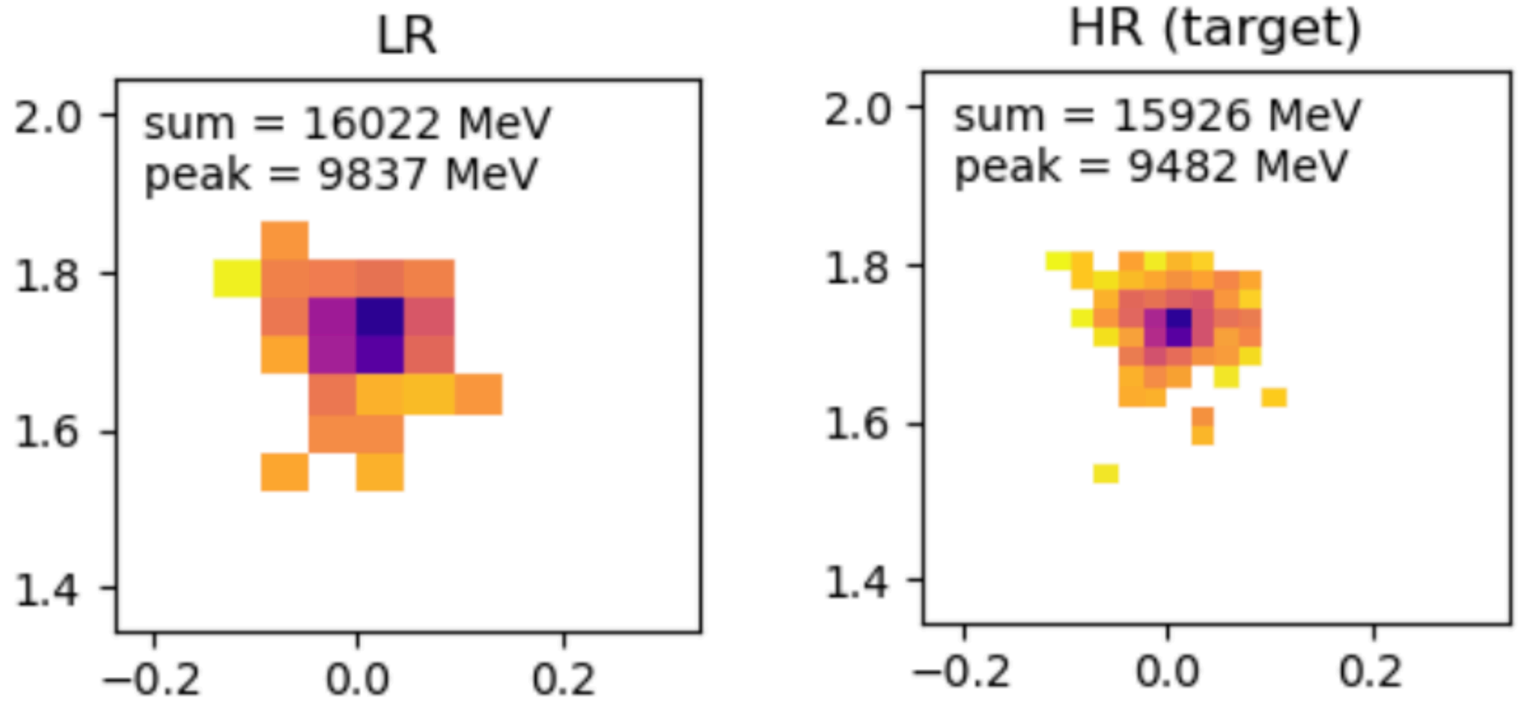
Super Resolution or ***Hallucination?***



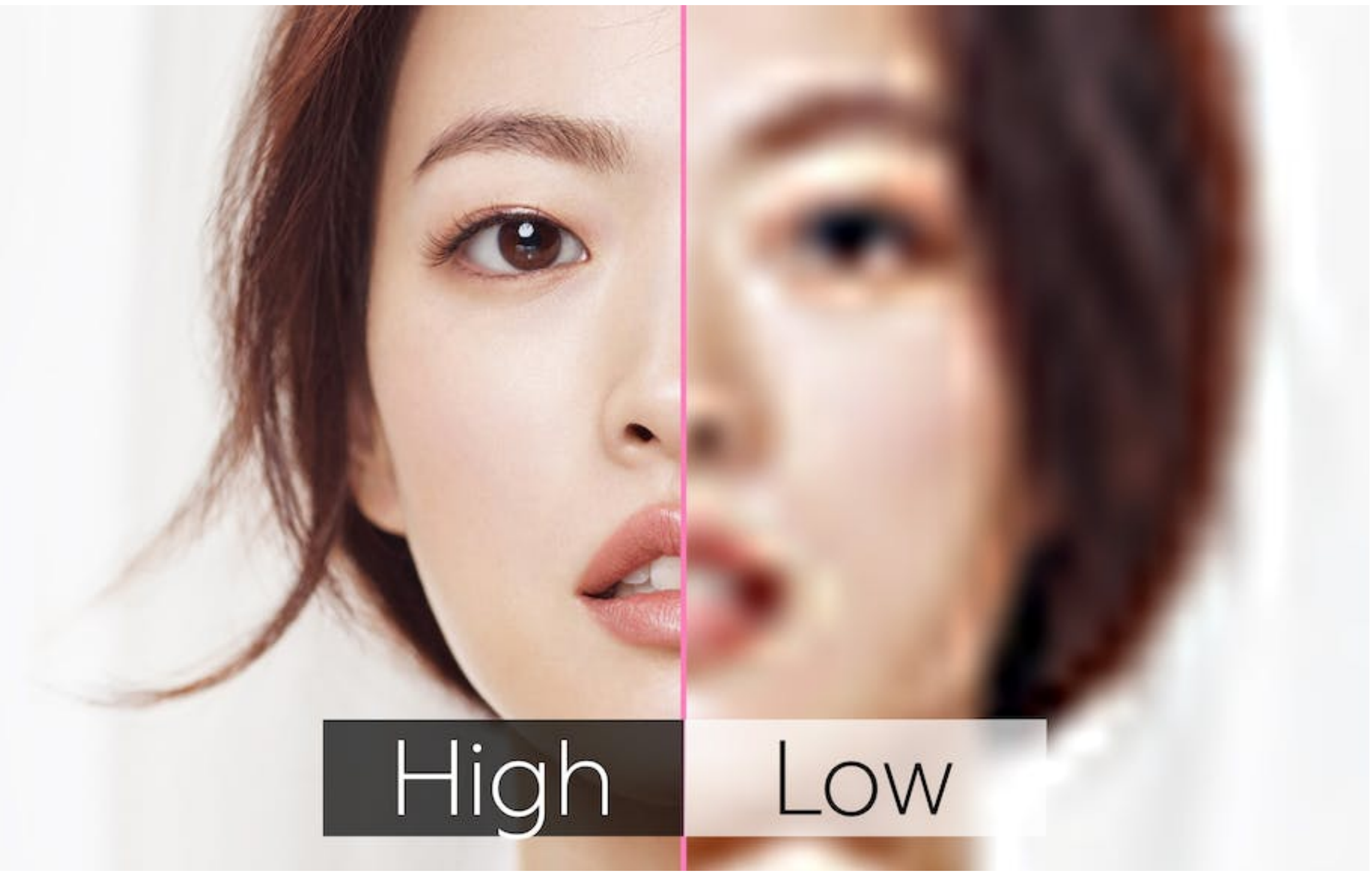
Where does the extra info come from?

Where does the extra info come from?

- From training data! *(Like any other ML algo)*
  - Energy deposition, by let's say a photon, is not random
  - Model can learn the HR distribution conditioned on the LR distribution



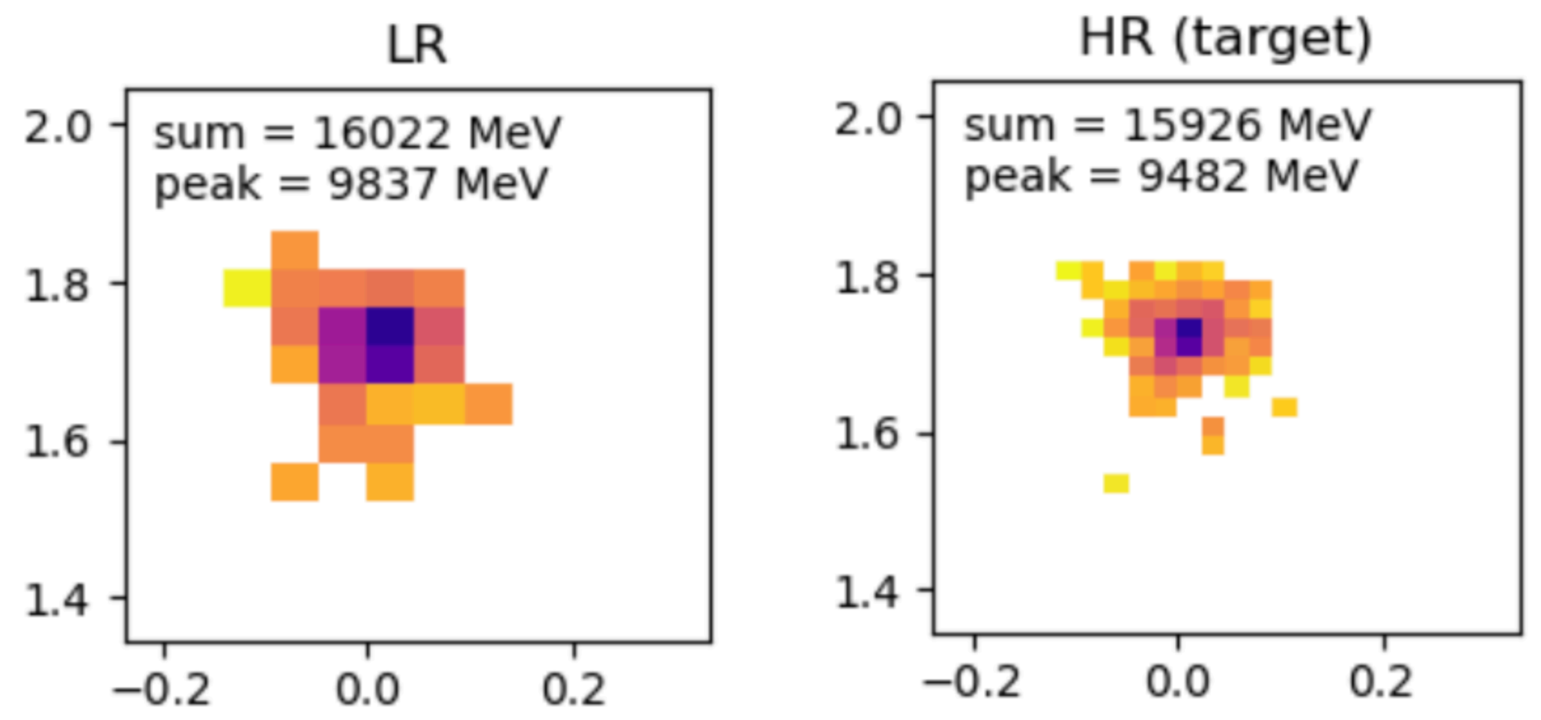
- HR output = Educated estimation of the model based on the patterns learned from the training data
  - Similar to how SR work in Computer vision



Ok, it ***can*** learn, but how do we know it ***is*** learning?

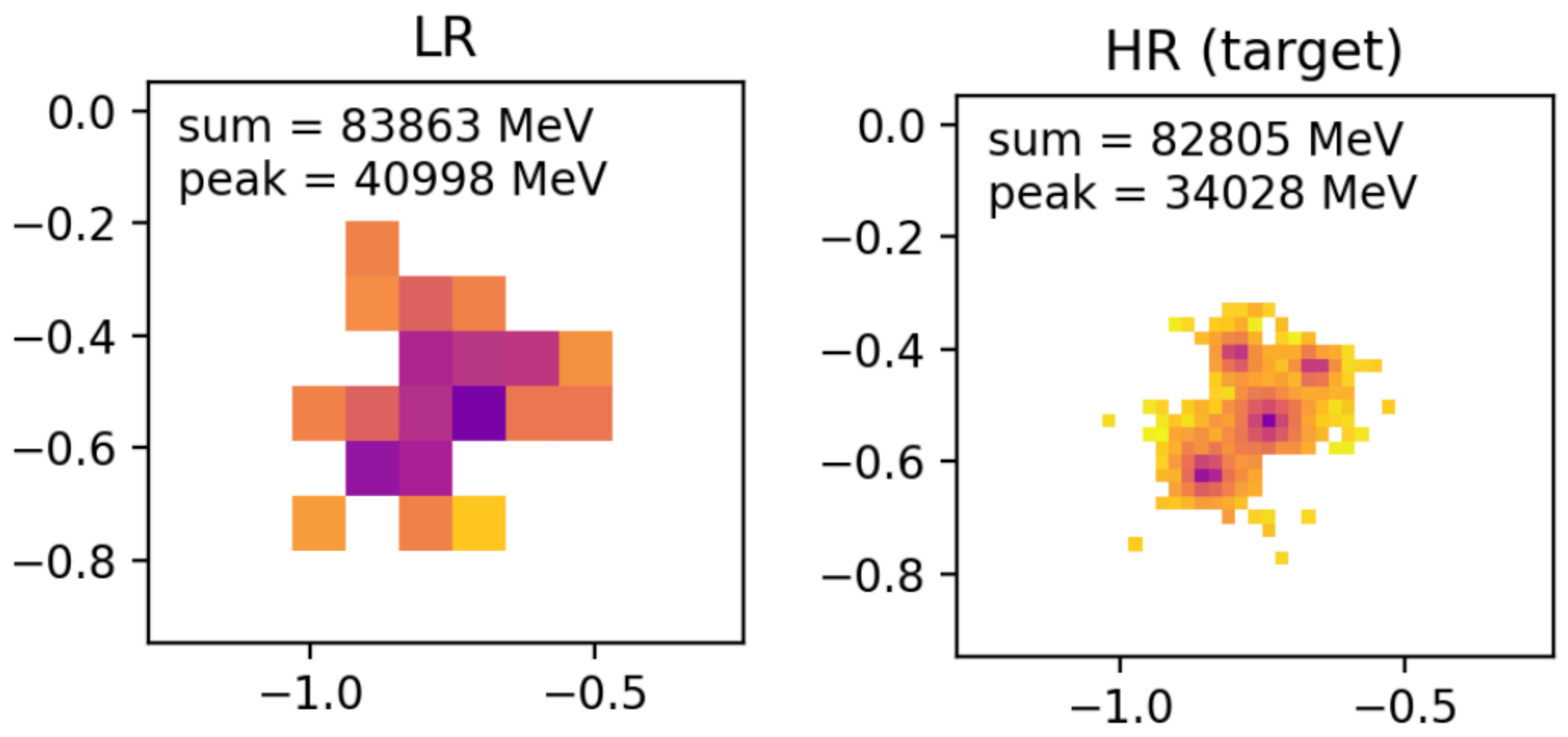
Ok, it *can* learn, but how do we know it *is* learning?

- Qn: The model can predict “realistic looking” outputs, but are they correct?
- With simulation,
  - Easy to check. we can have the truth targets
- With actual data,
  - Not so easy. (How much we trust our simulations?)
  - Calibration problem (tricky, but should be doable)



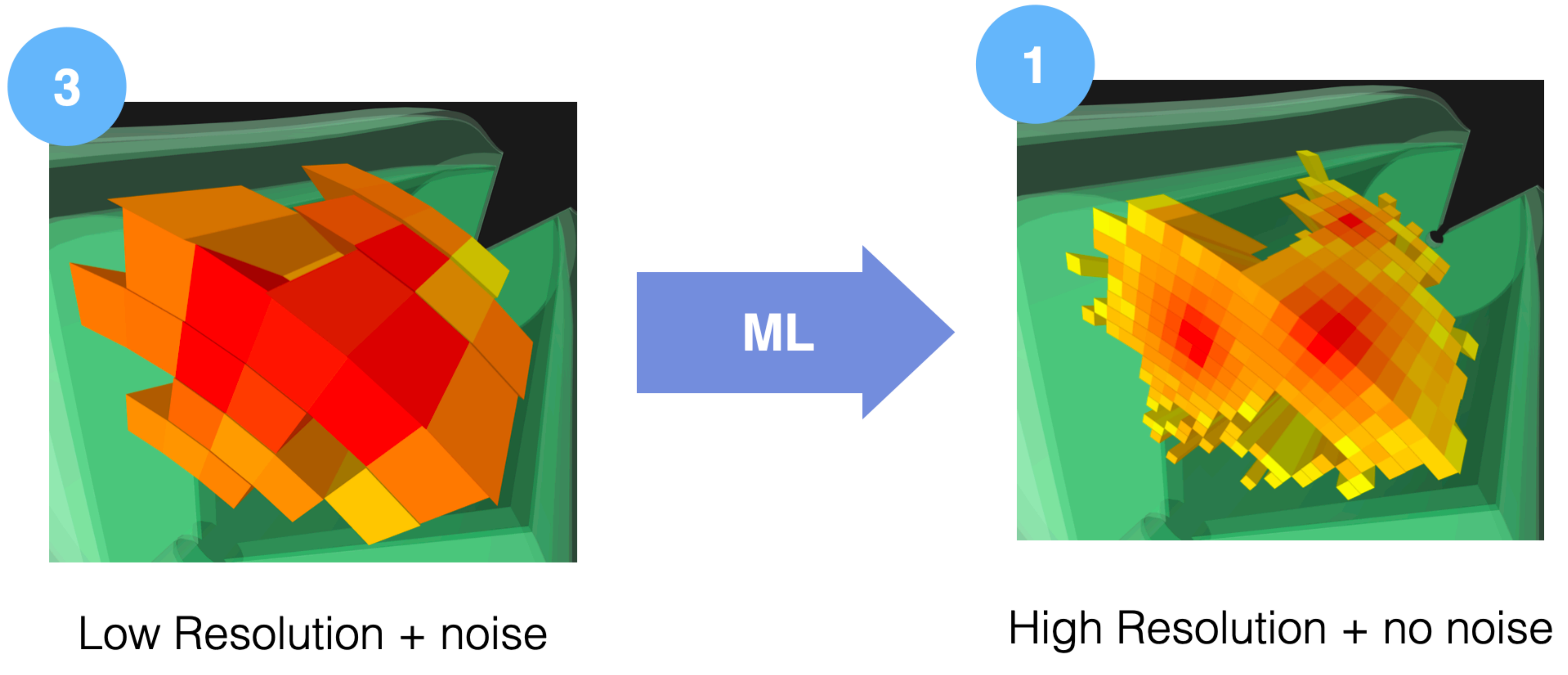
But, most importantly,

- We shouldn't look at it in isolation
- Primary goal -
  - Improve reconstruction
  - Super resolution is just an auxiliary task



Wrapping up…

- AI super resolution magic can actually work!
  - We can *"pretend"* to have a higher-resolution detector and the reconstruction performance reflects it.
- Primary future extensions
  - More particles (full event)
  - Including the hadronic calorimeter

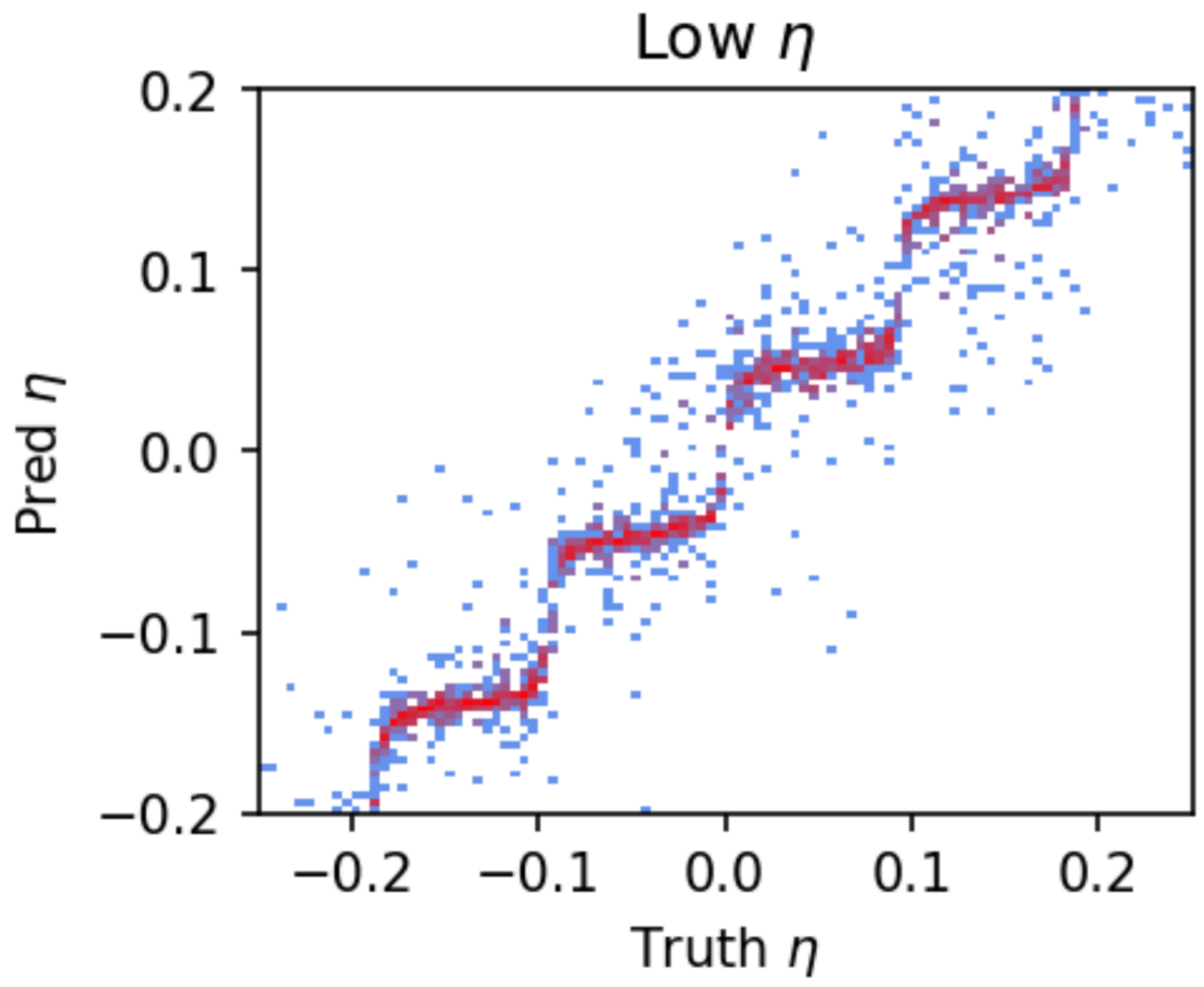


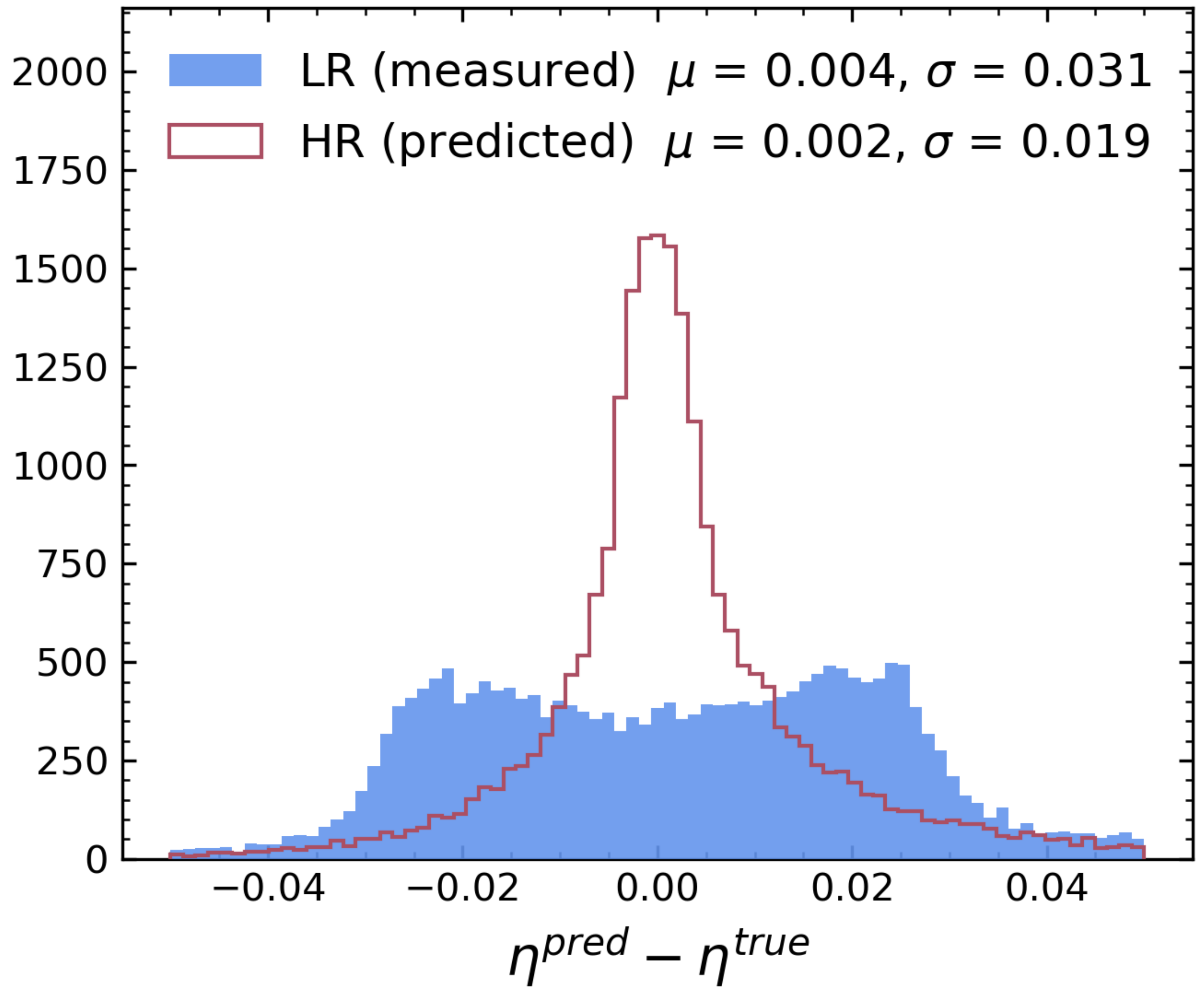
- Can help current reconstructions
- Specifically, can be helpful for future detector designs
- arXiv preprint: https://arxiv.org/abs/2409.16052

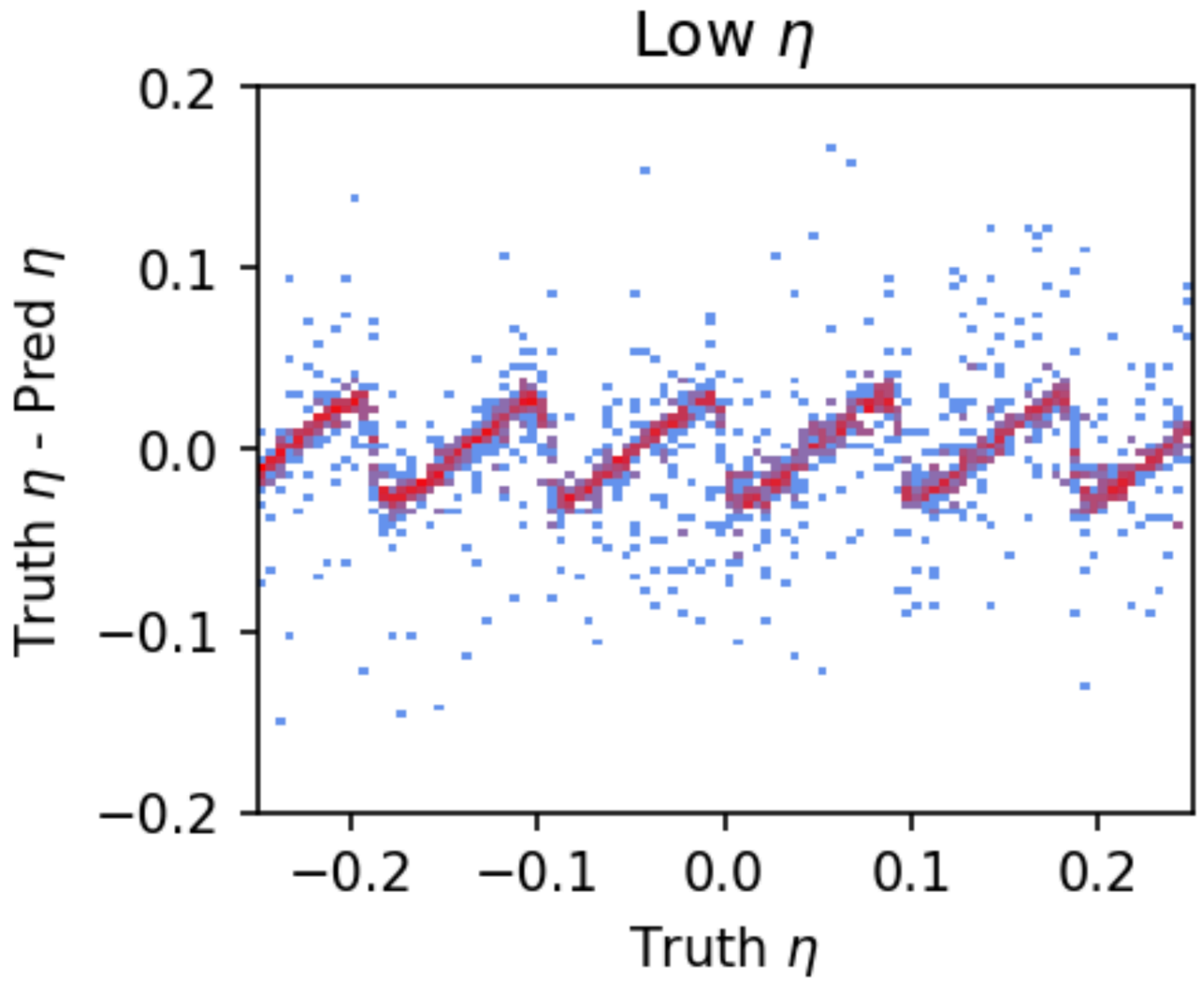
Thanks!

Backup

Understanding η, ϕ residuals

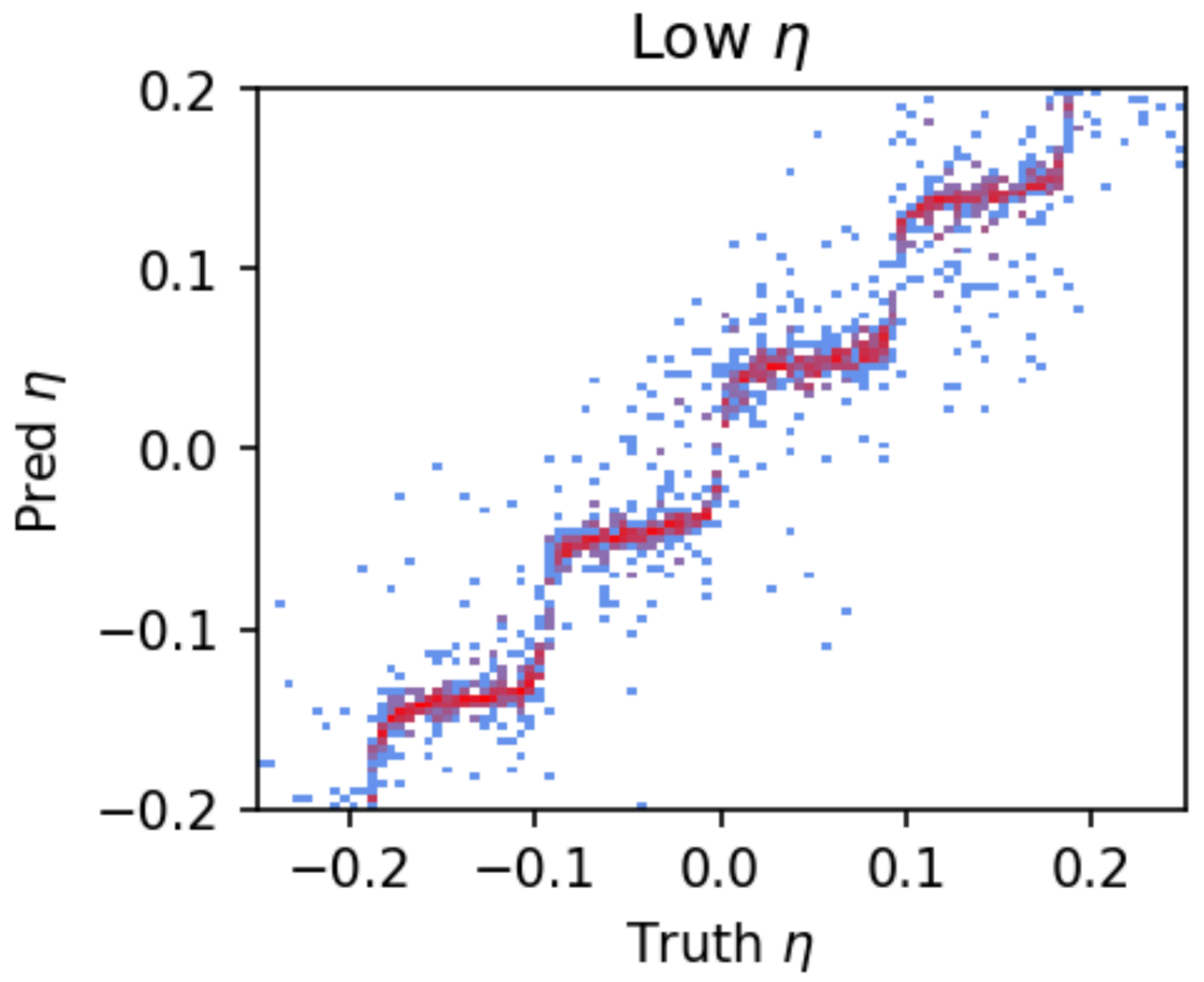


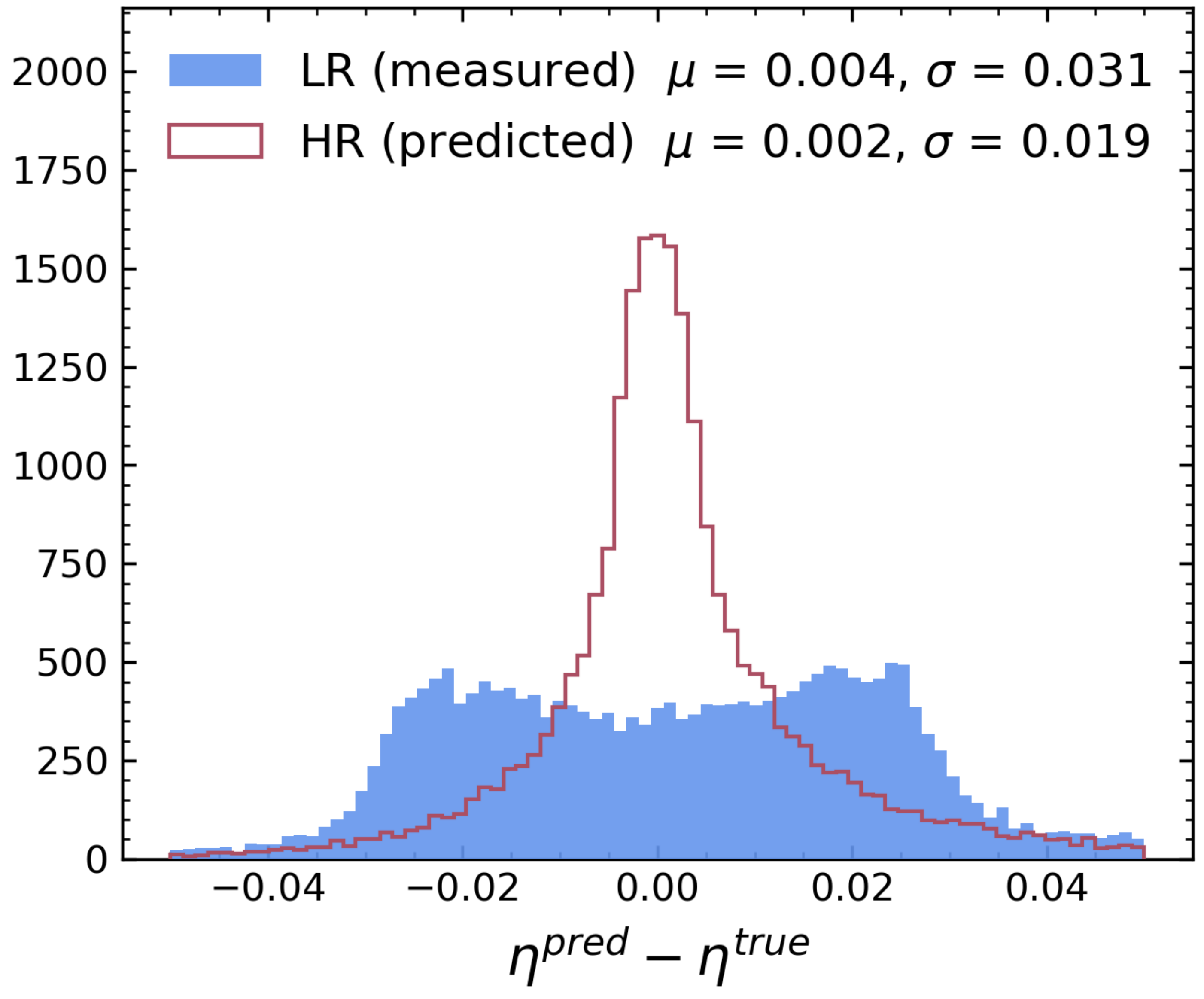


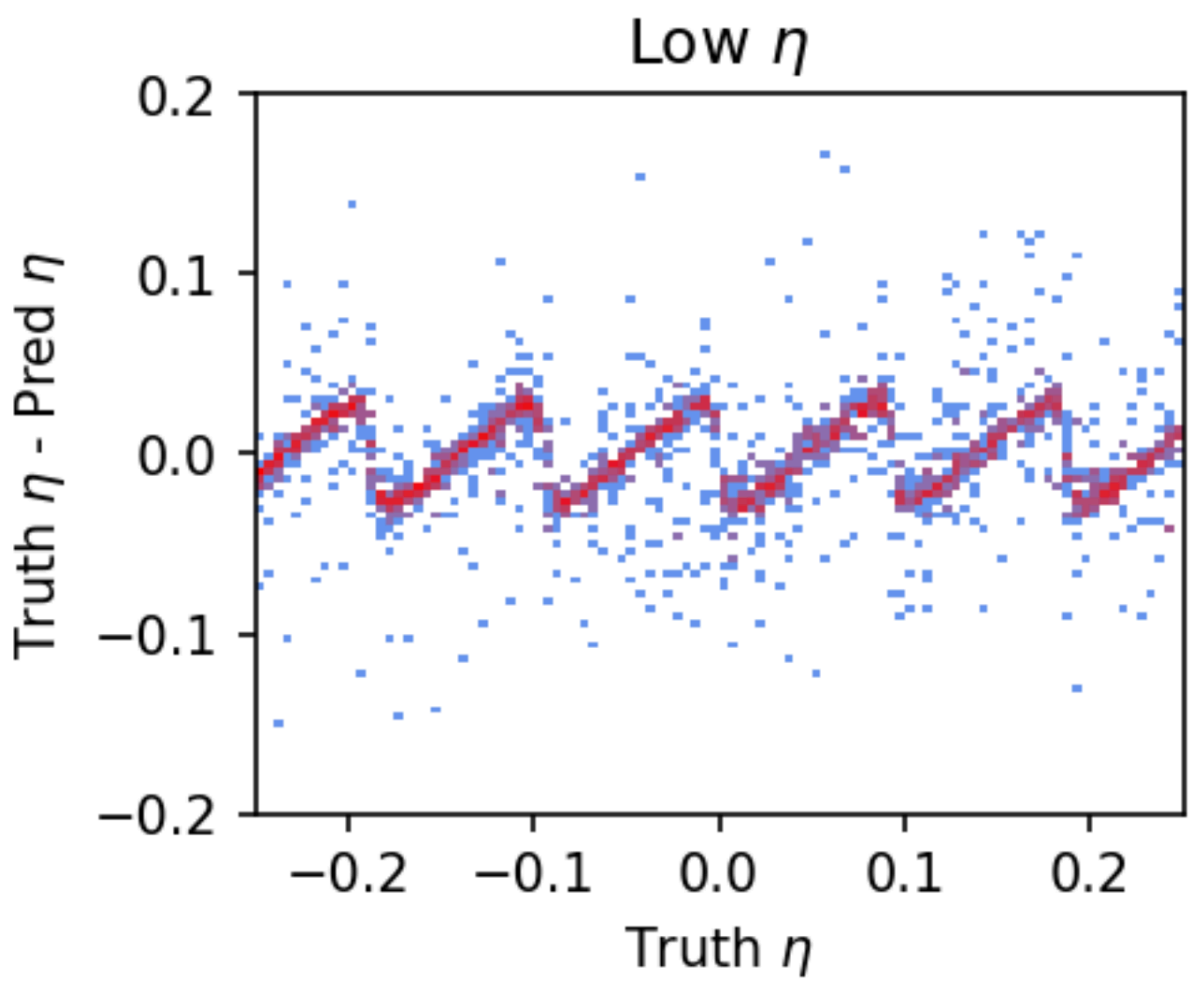


Understanding η, ϕ residuals

- Network predicts for each cell how much it's associated to each particle







Understanding η, ϕ residuals

- Network predicts for each cell how much it's associated to each particle

- $$\text{particle } \eta = \sum_i w_i \cdot \text{cell}_i \ \eta$$