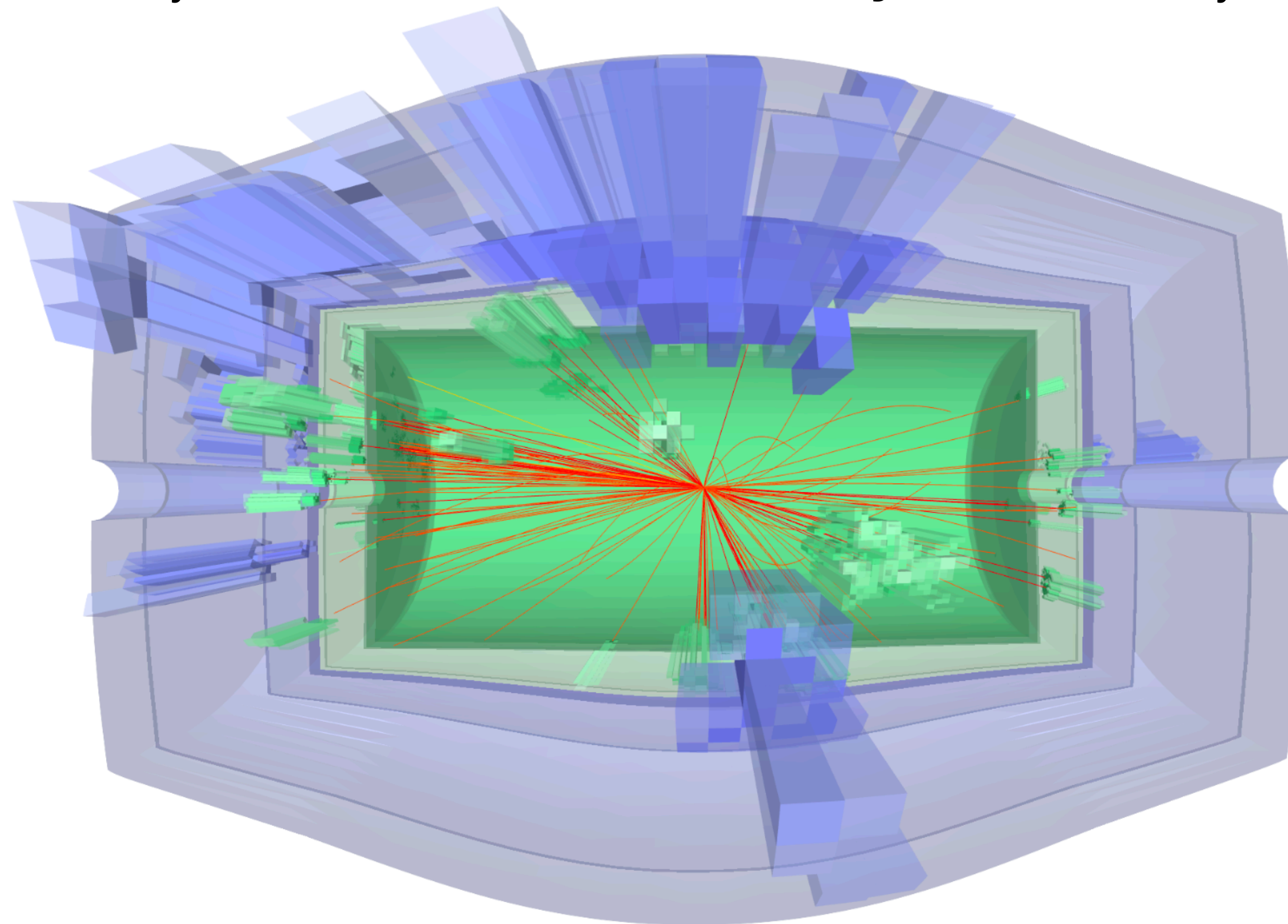
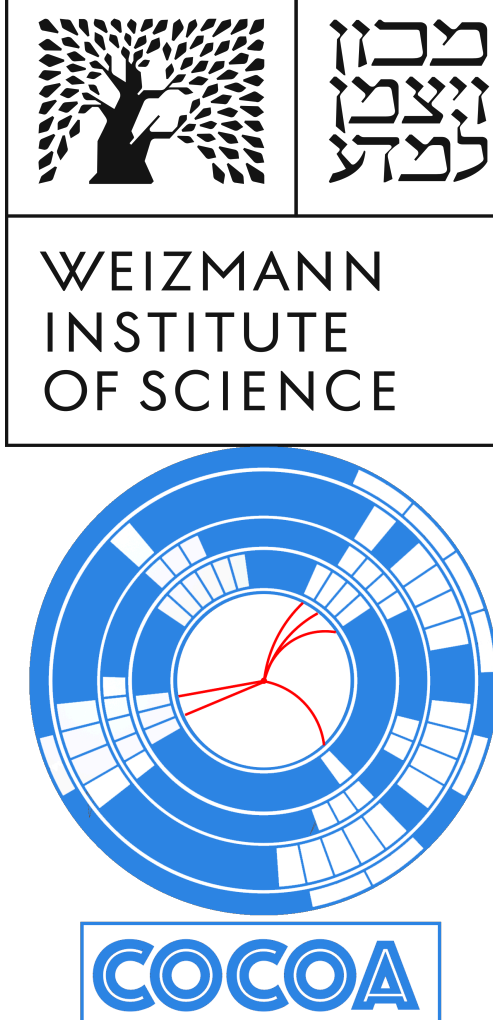
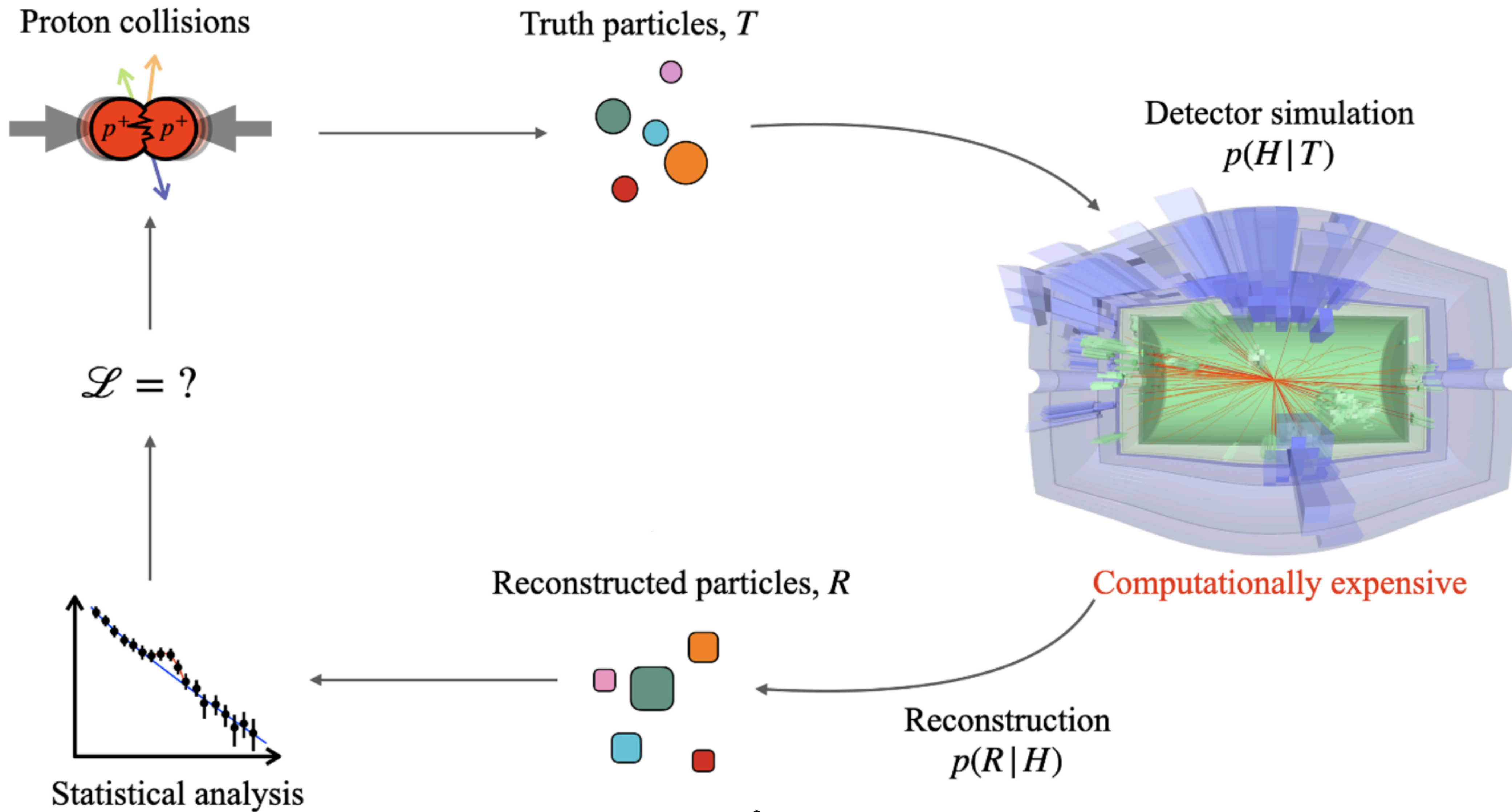


# Fast Simulation using Graph Diffusion and Graph-to-Graph Translation

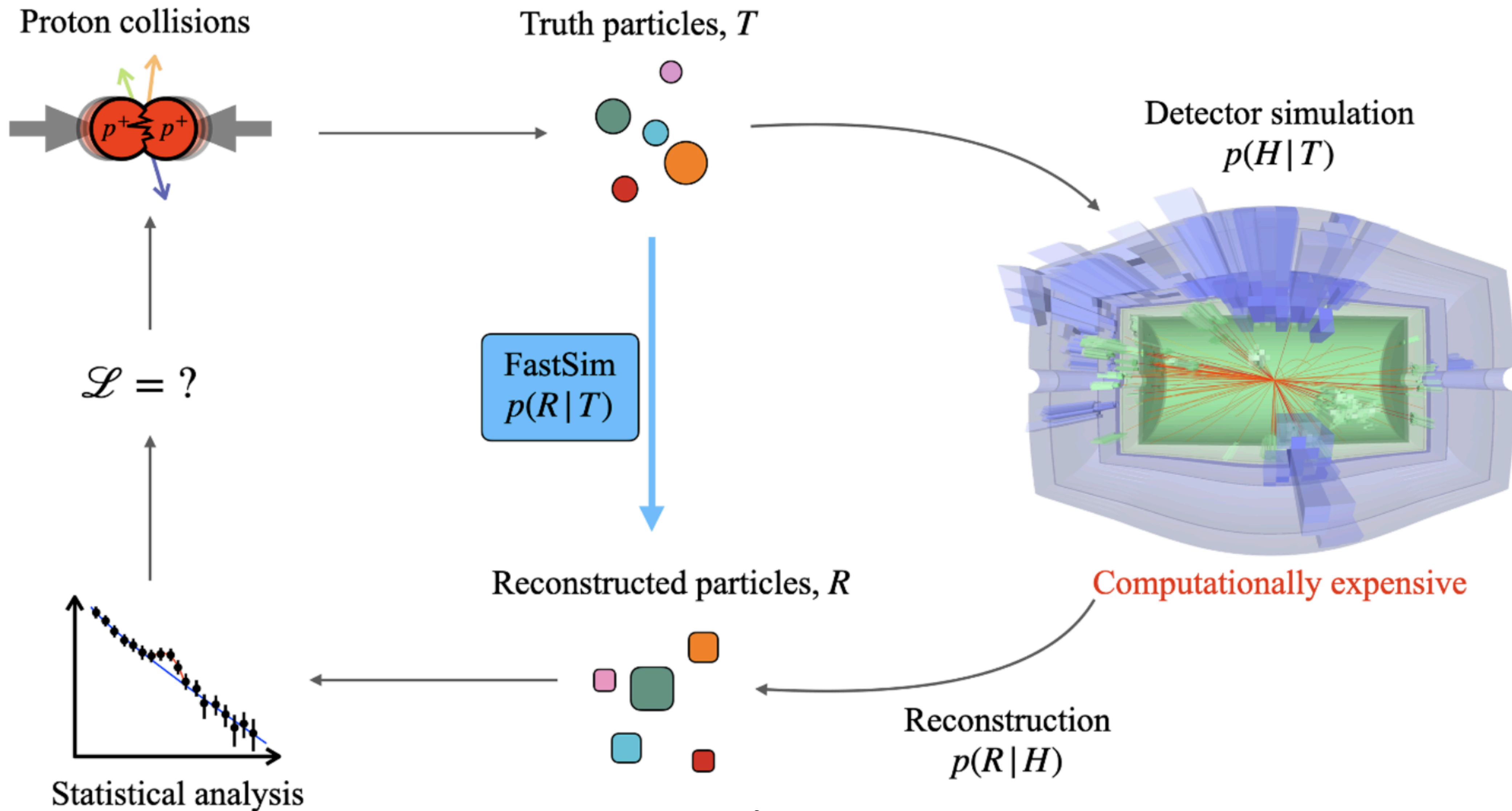
E. Dreyer, E. Gross, N. Kakati, **D. Kobylanski**, N. Soybelman



# Motivation



# Motivation



# Previous work

arXiv: [2211.06406](https://arxiv.org/abs/2211.06406)

ACCEPTED MANUSCRIPT • OPEN ACCESS

## Set-Conditional Set Generation for Particle Physics

Nathalie Soybelman<sup>1</sup>, Nilotpal Kakati<sup>1</sup>, Lukas Heinrich<sup>2</sup> , Francesco Armando Di Bello<sup>3</sup>,  
Etienne Dreyer<sup>1</sup>, Sanmay Ganguly<sup>4</sup>, Eilam Gross<sup>1</sup>, Marumi Kado<sup>5</sup> and Jonathan Shlomi<sup>6</sup> 

Accepted Manuscript online 13 October 2023 • © 2023 The Author(s). Published by IOP Publishing Ltd

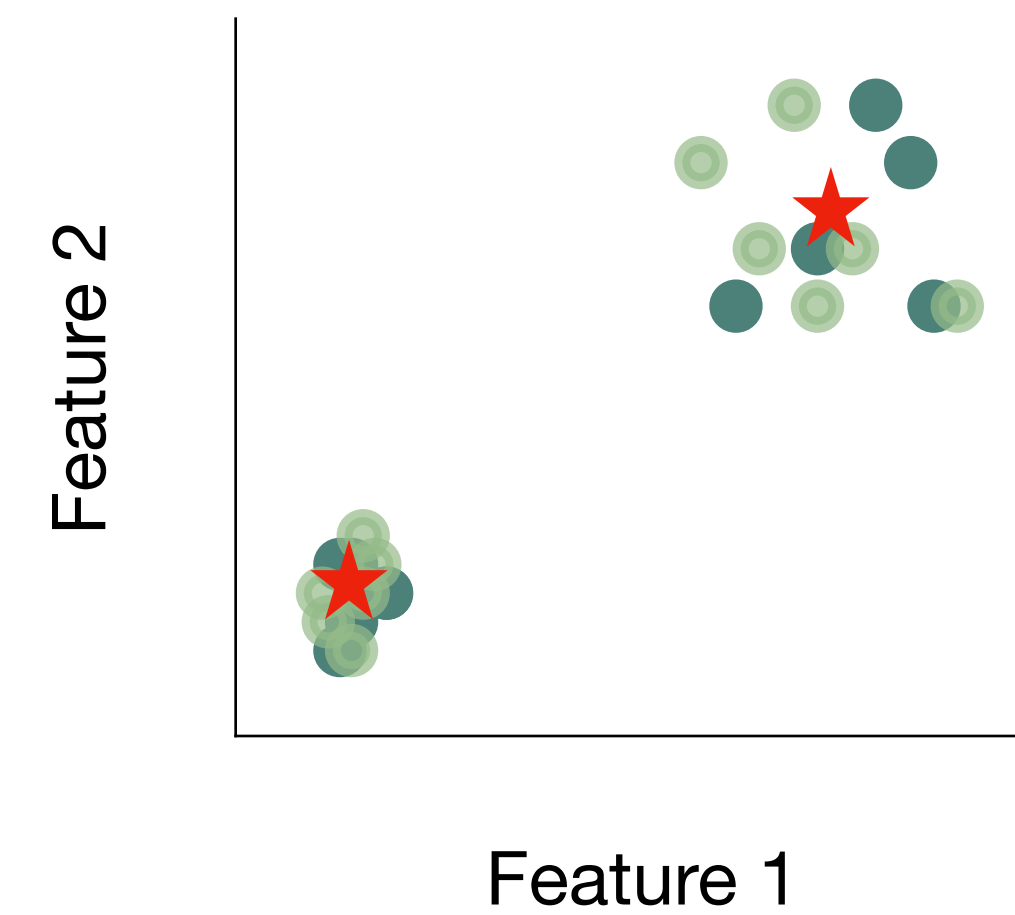
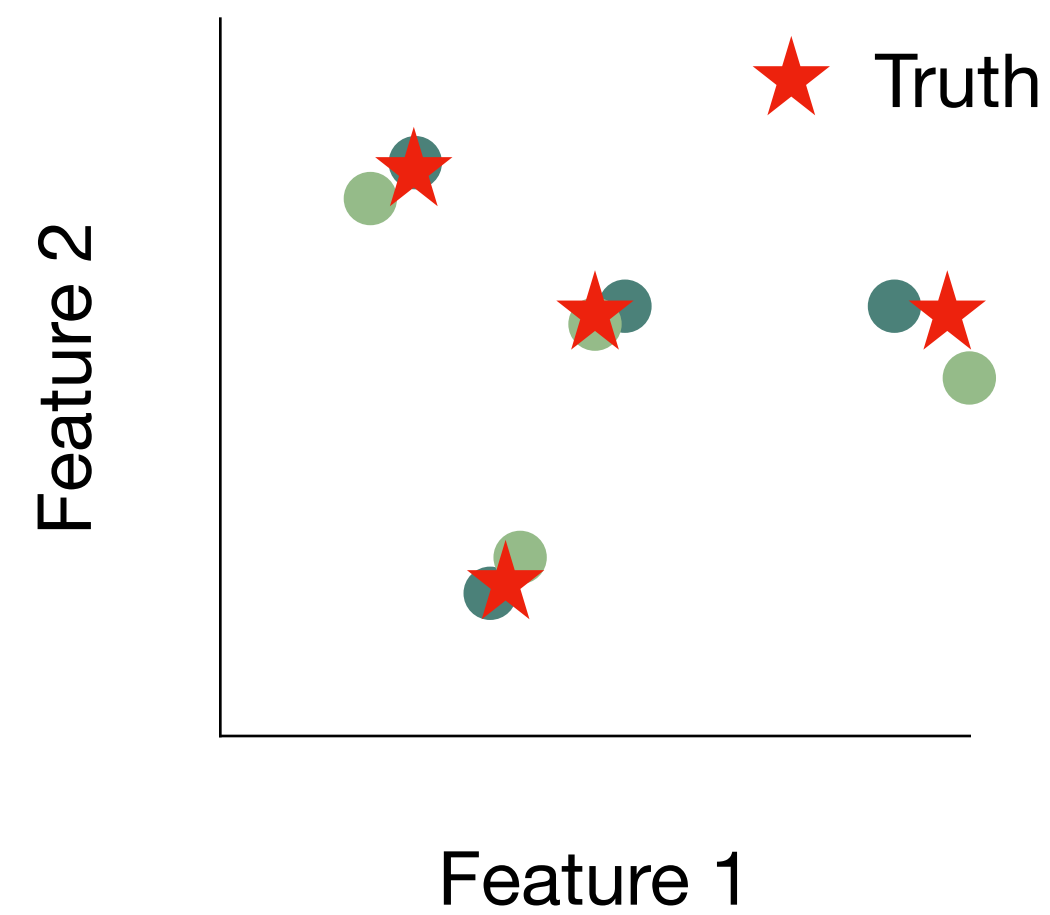
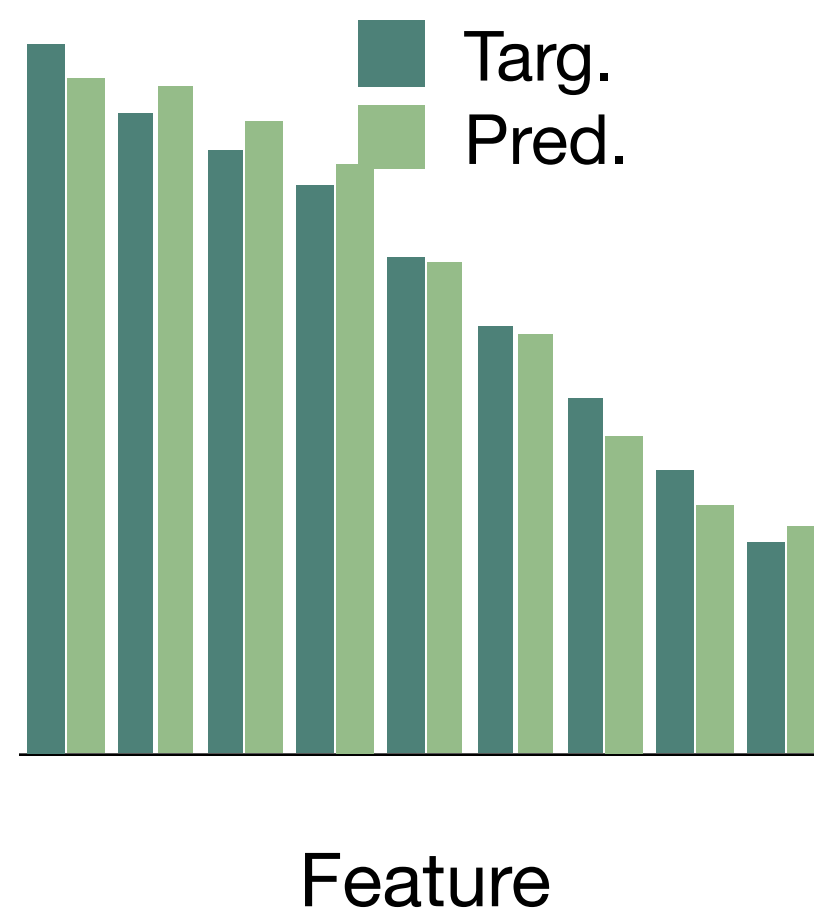
	Previously	Now
Dataset	Toy model — emulated tracks	Full simulation & reconstruction
Particles	charged only	charged + neutral
Architecture	GNN with Slot-Attention	Graph Diffusion Graph-to-Graph Translation

# Goals

Marginal  
distributions

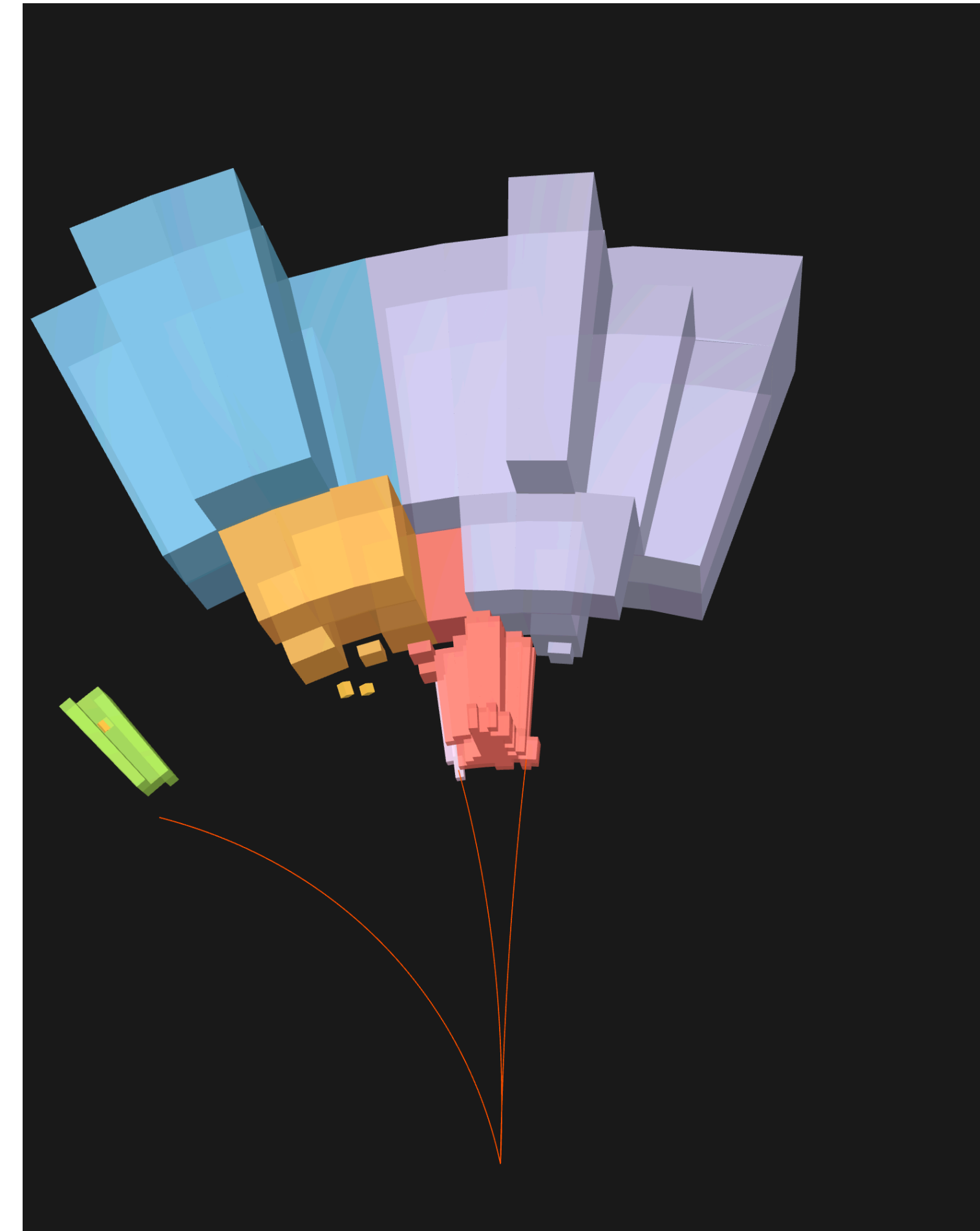
Reconstruct  
constituents

Resolution

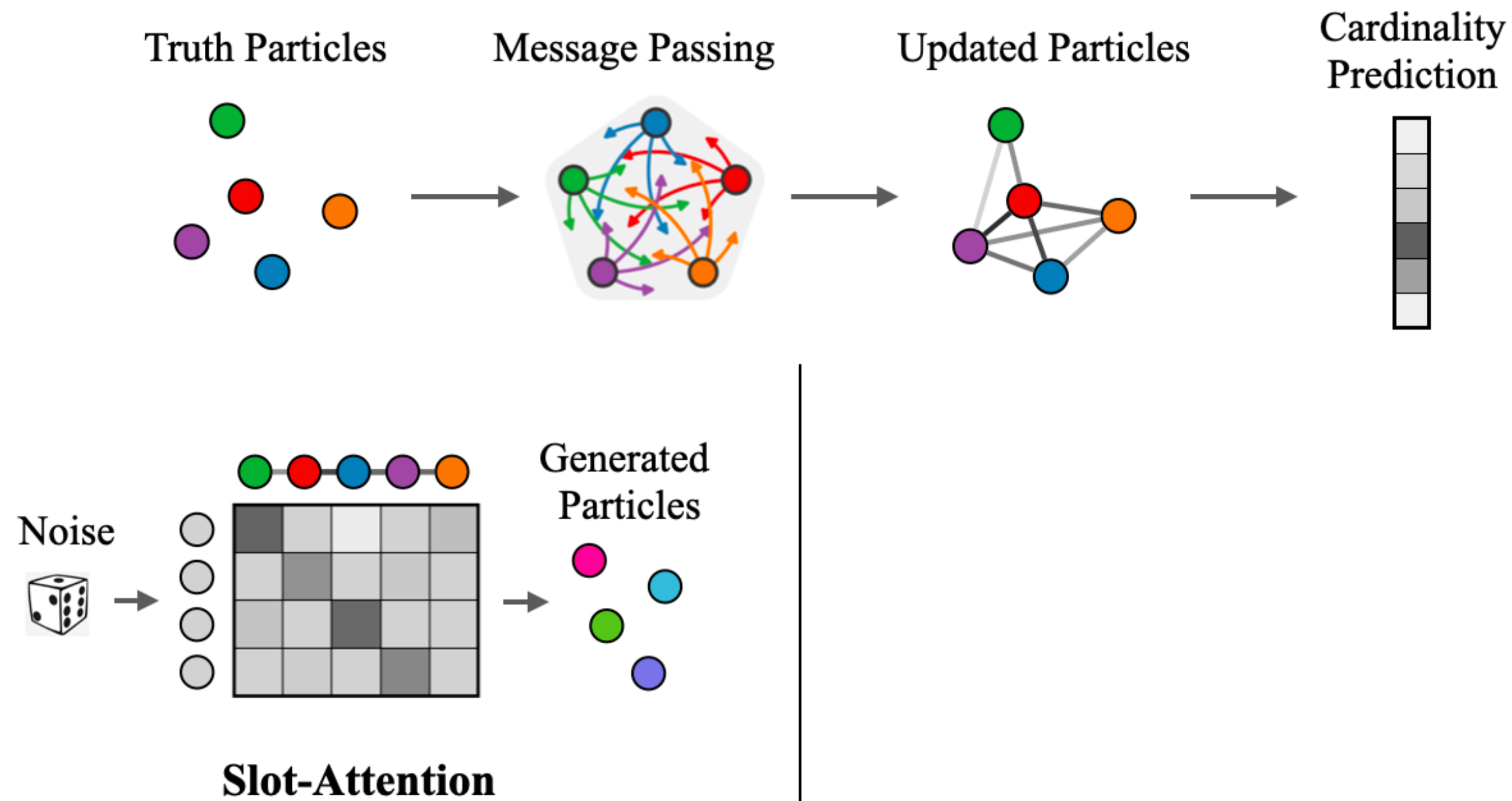


# Dataset

- Single jet events
- COCOA detector simulation — [2303.02101](#)
- HGPflow reconstruction — [2212.01328](#)
- **100 replicas** per event  
repeat detector simulation for the same truth event

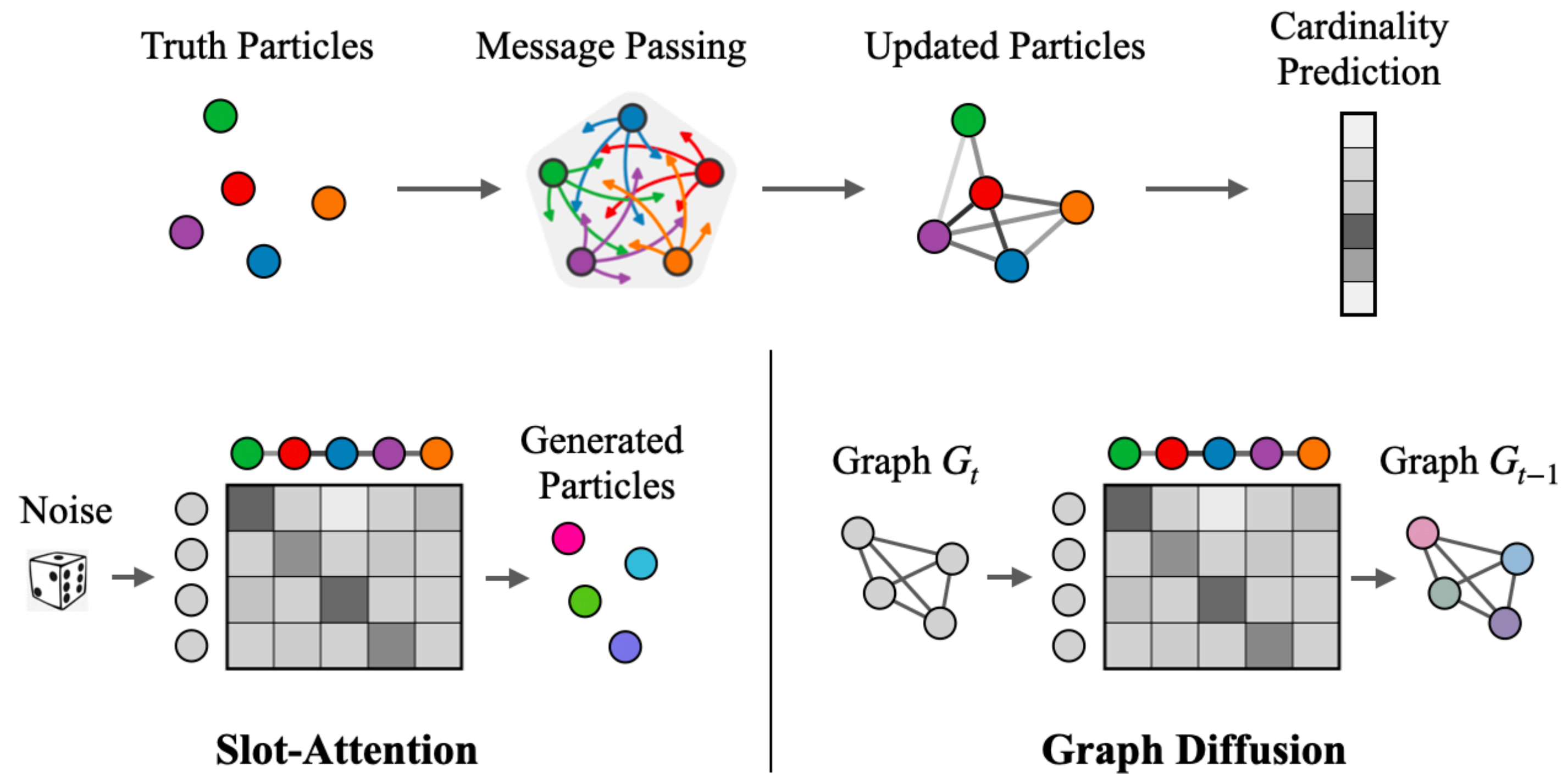


# Architectures



Set-based loss through Hungarian matching (LSA) using particle features

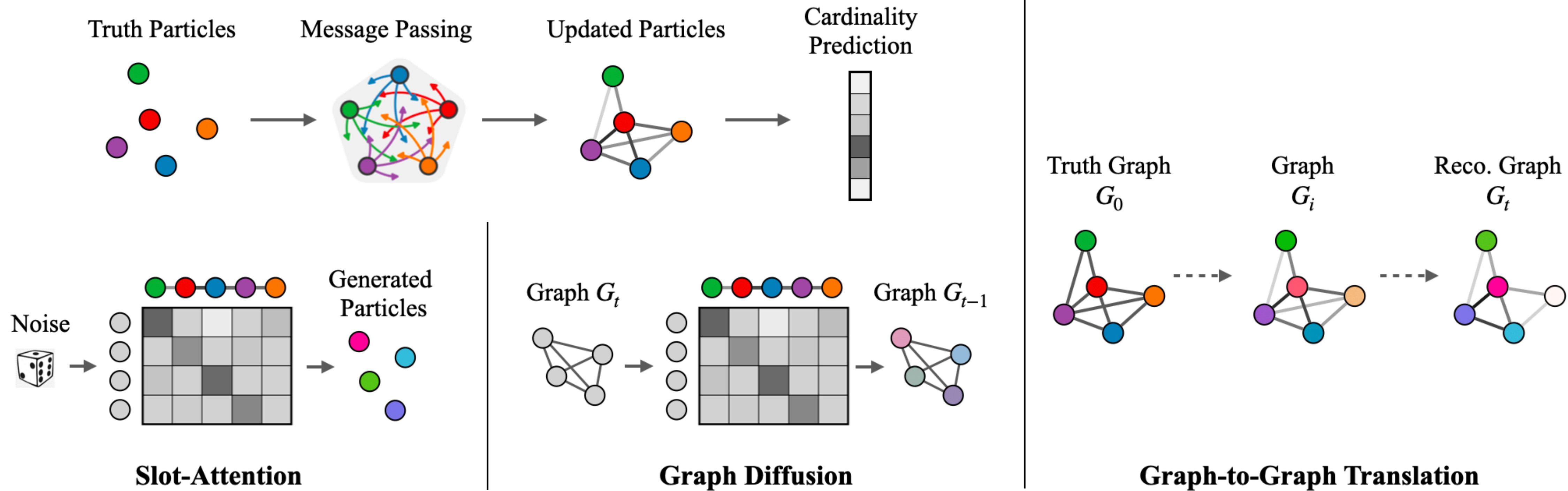
# Architectures



Set-based loss through Hungarian matching (LSA) using particle features

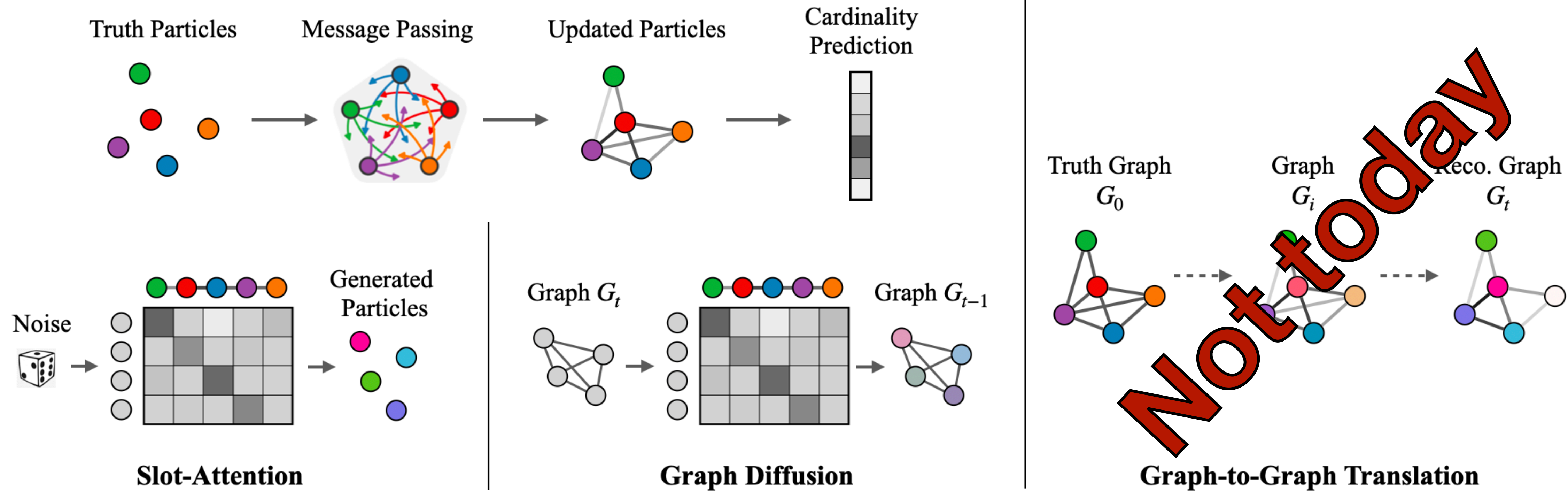


# Architectures



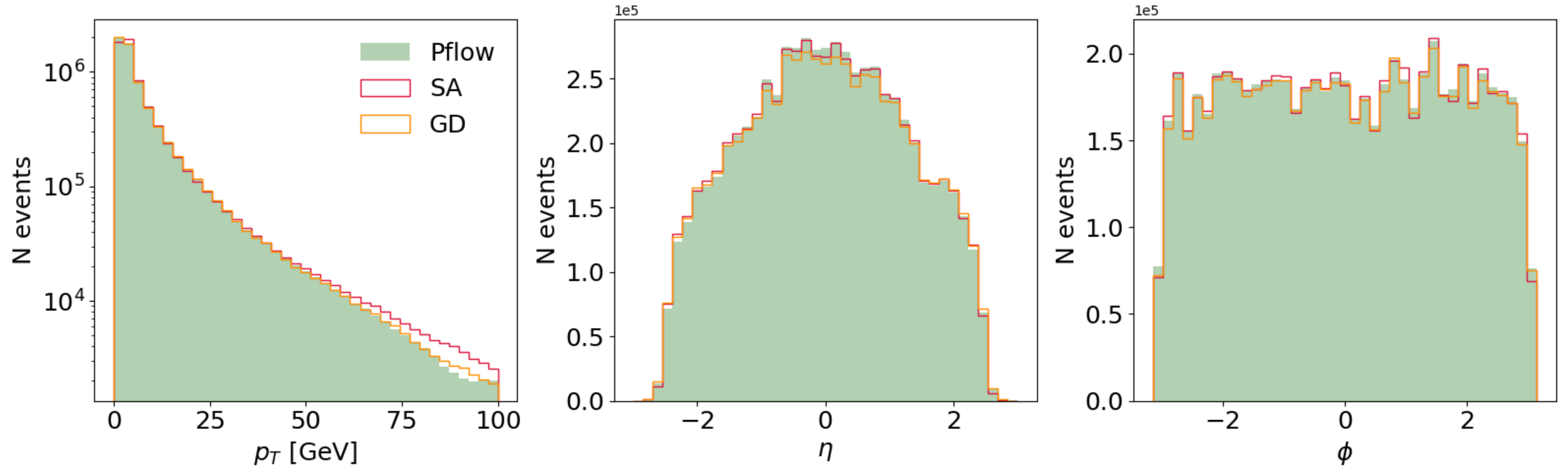
Set-based loss through Hungarian matching (LSA) using particle features

# Architectures



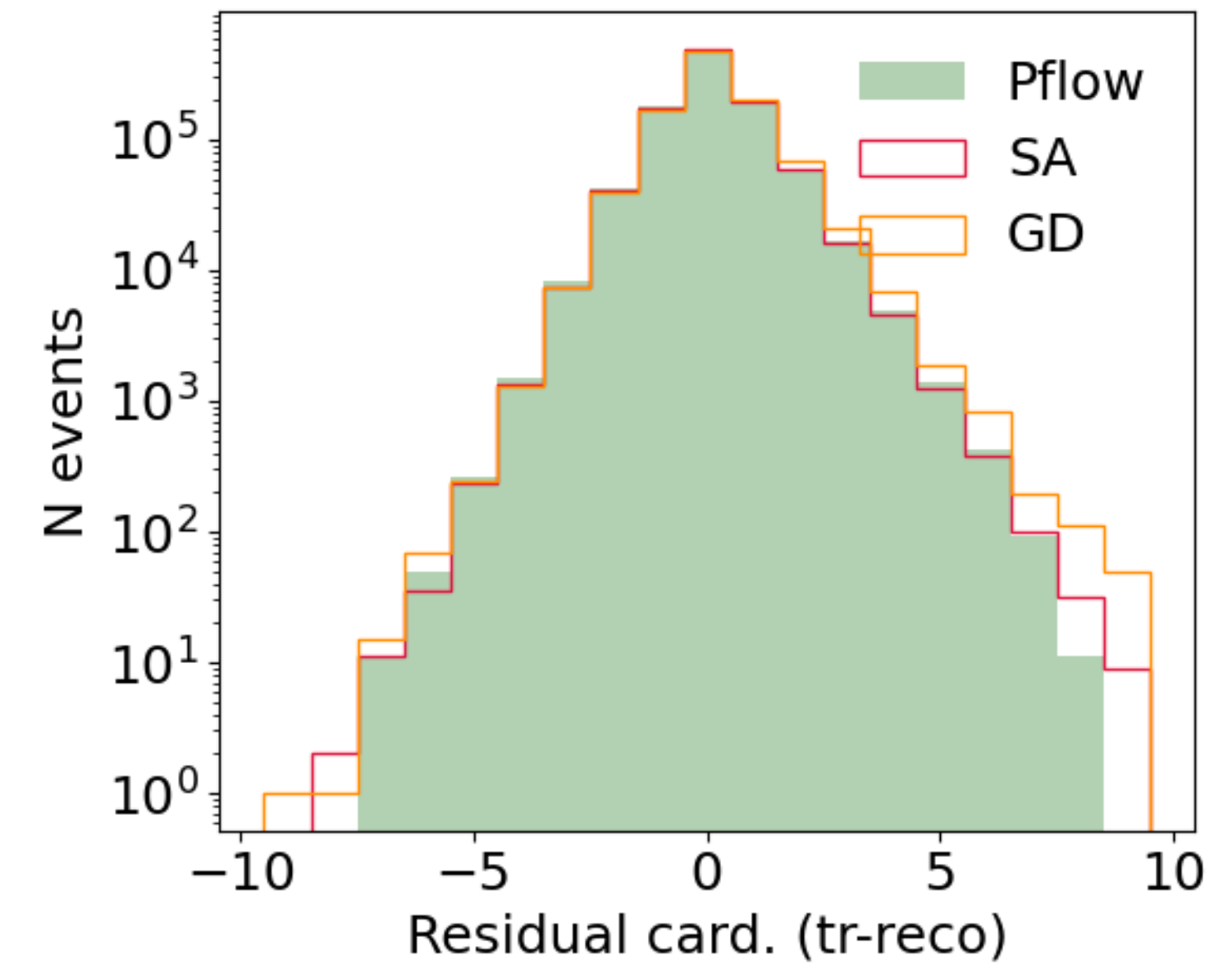
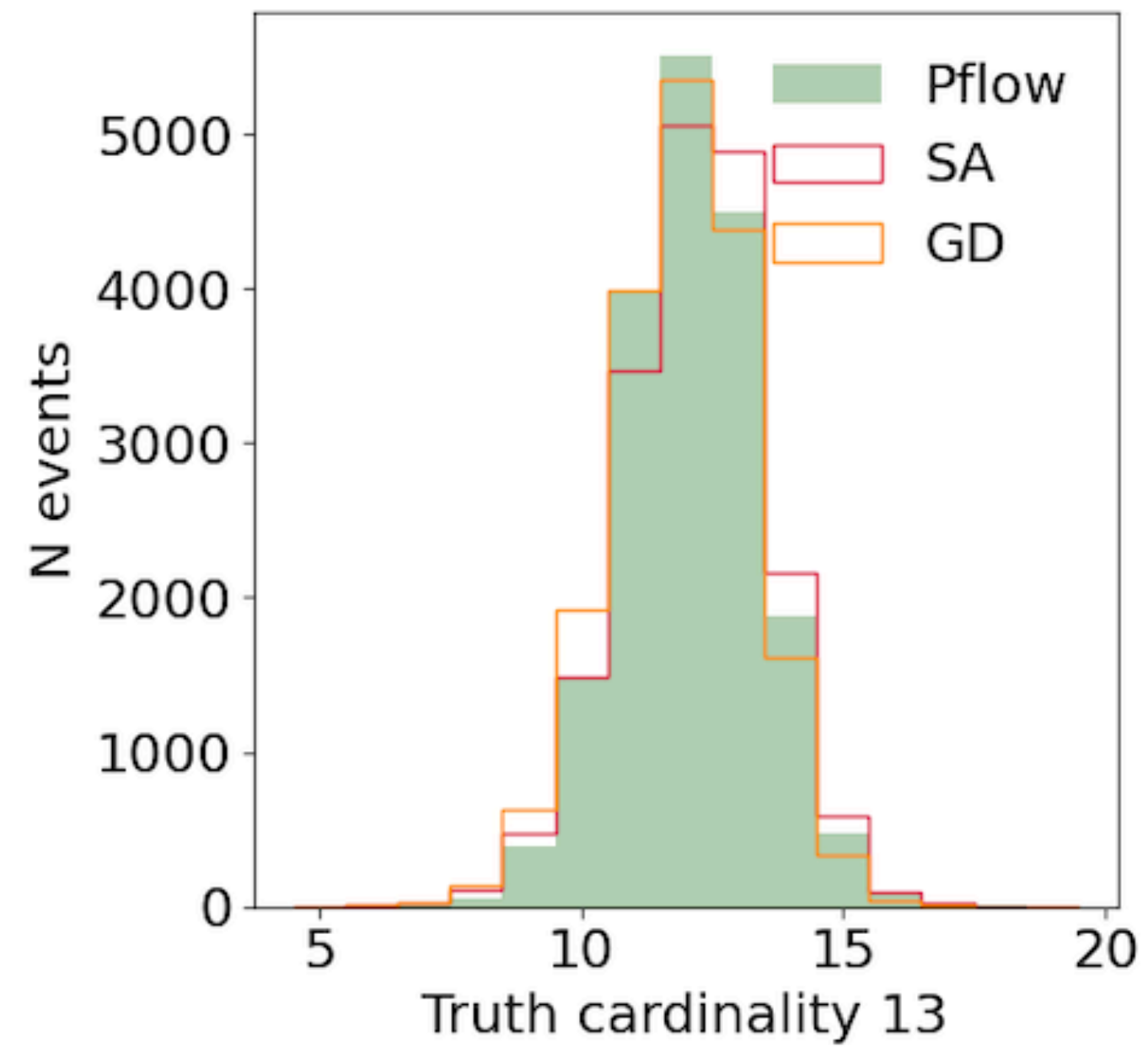
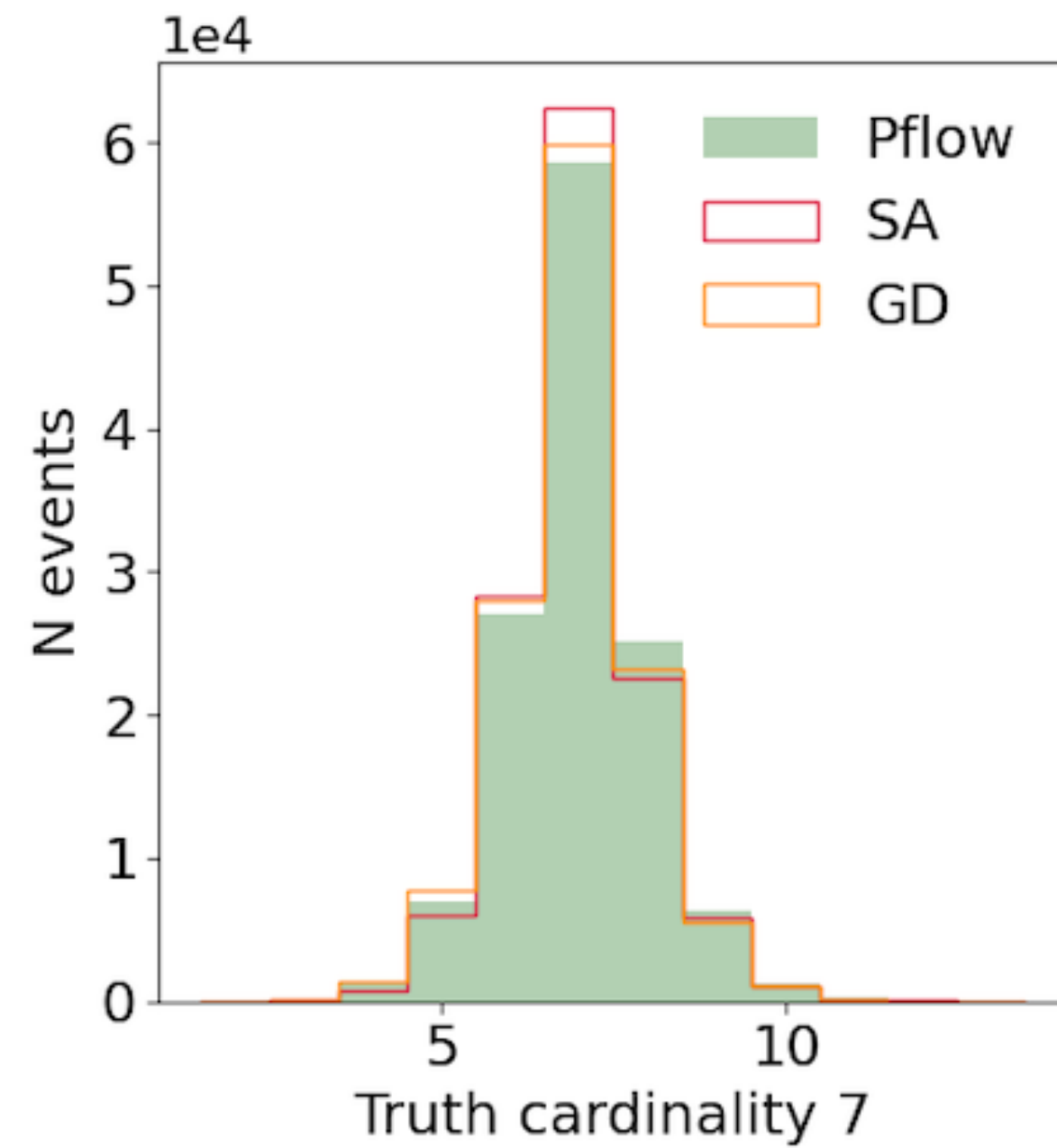
Set-based loss through Hungarian matching (LSA) using particle features

# Marginal distributions



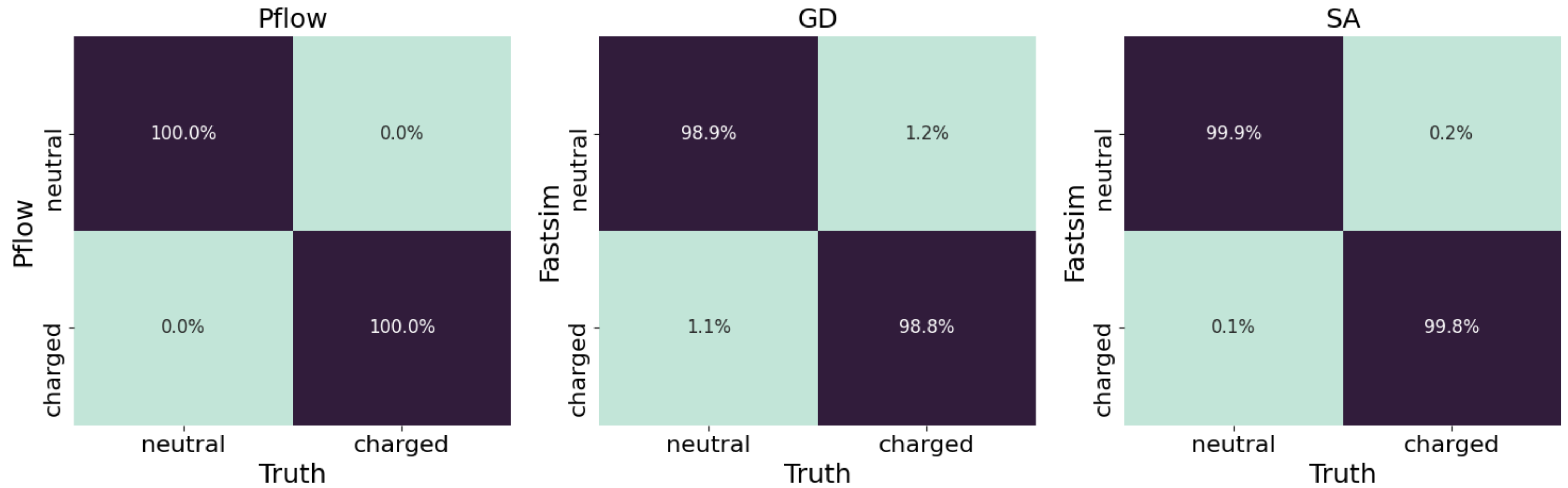
- Overall good agreement
- Some issues in  $p_T$  tail — under investigation

# Cardinality



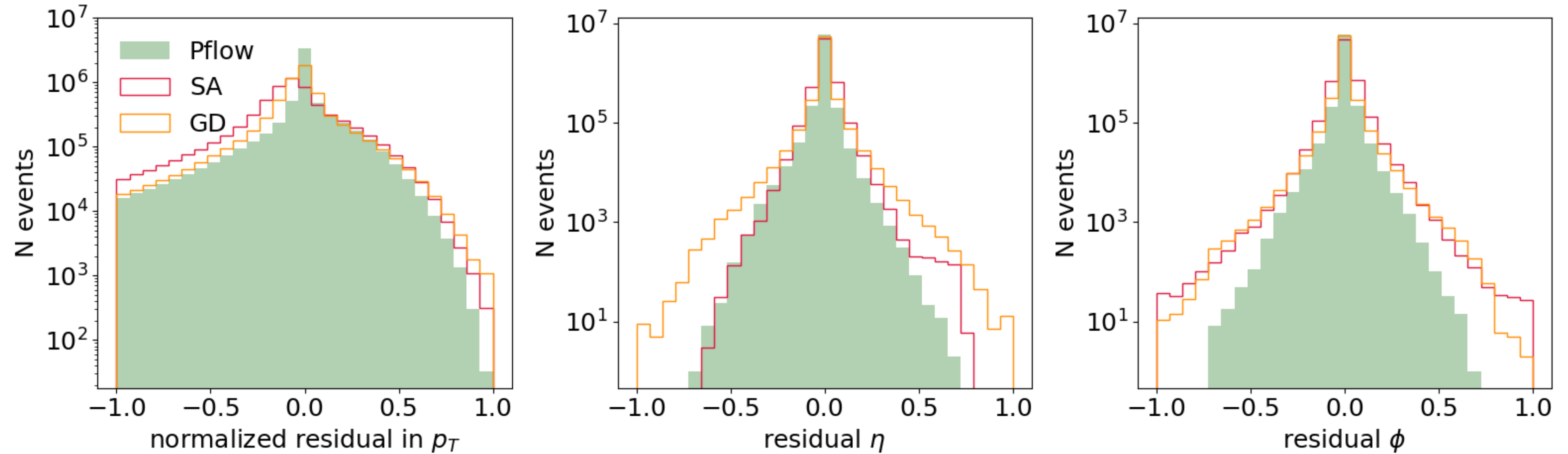
- Overall good match
- SA & GD very similar — expected since its the same network

# Class prediction

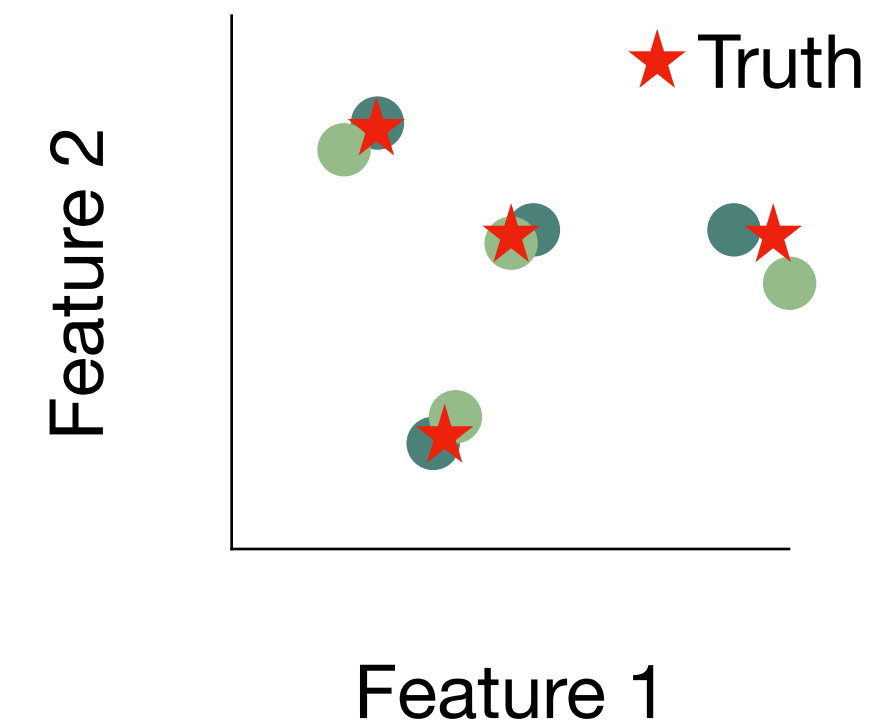


- Overall good match
- SA is better than GD

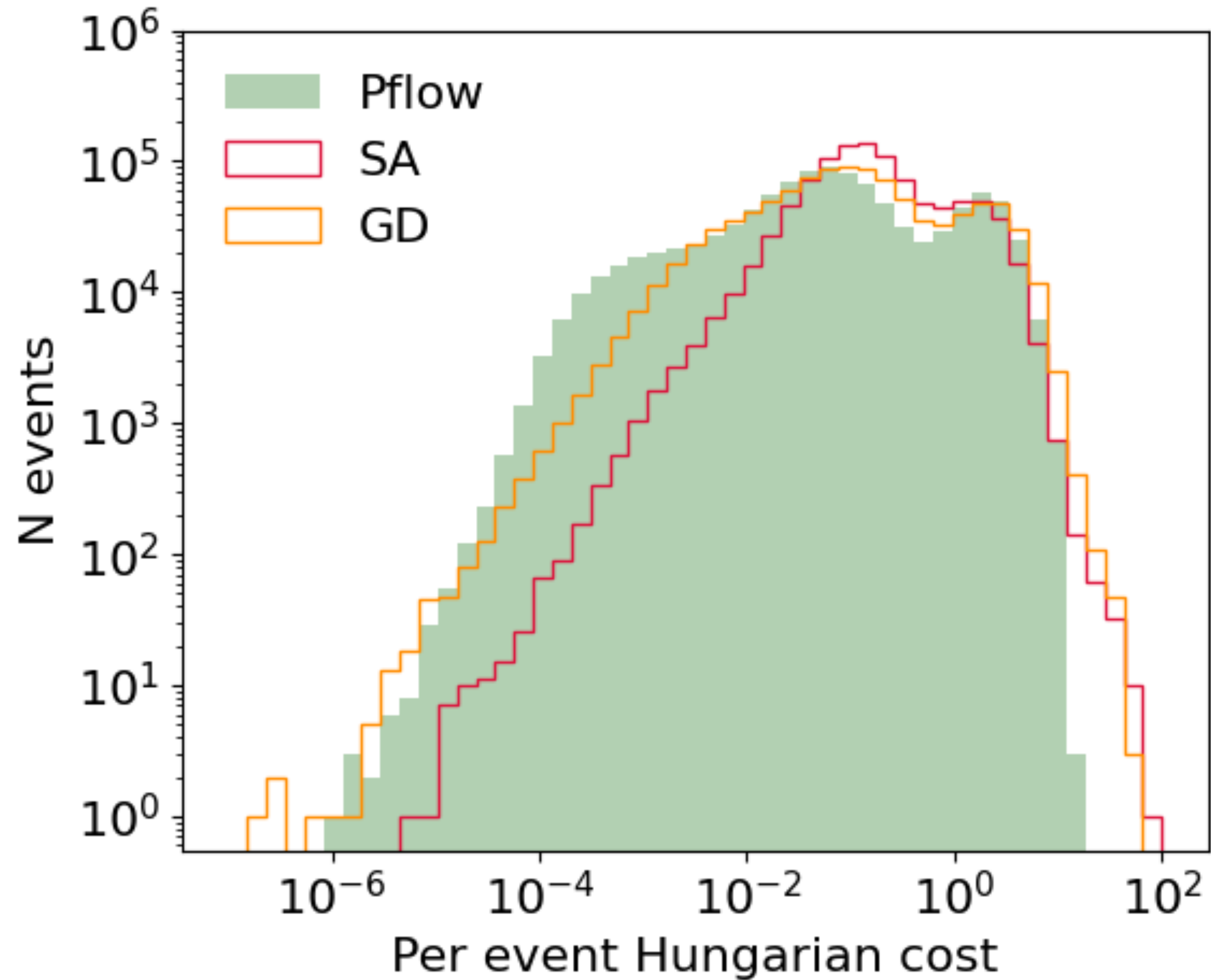
# Residuals – ‘Distance to Truth’



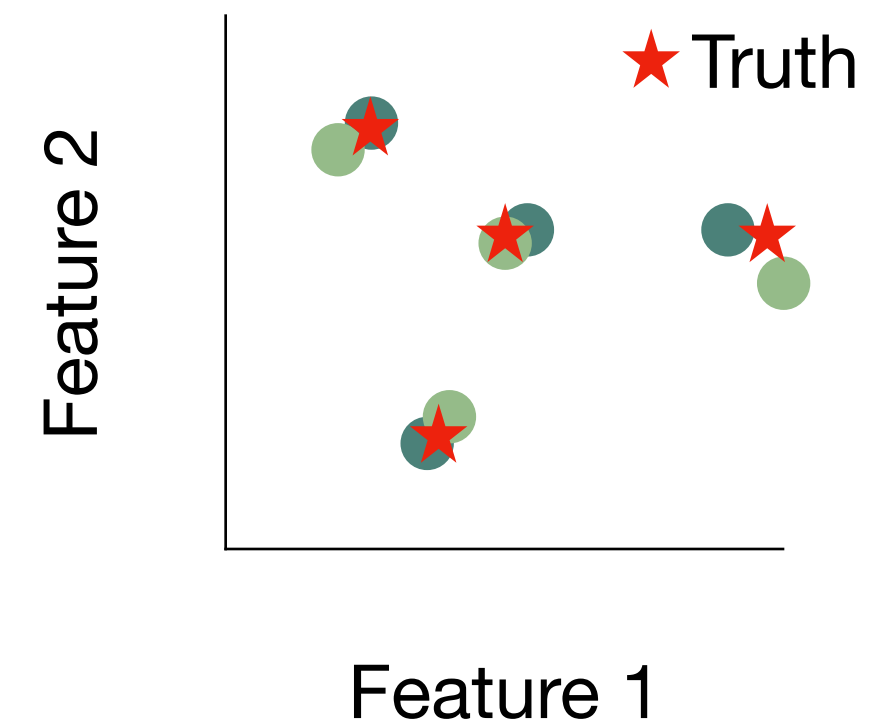
- Hungarian matching between truth and reconstruction
- GD has a good agreement in  $p_T$
- SA is a bit better in  $\eta$
- Need combined metric



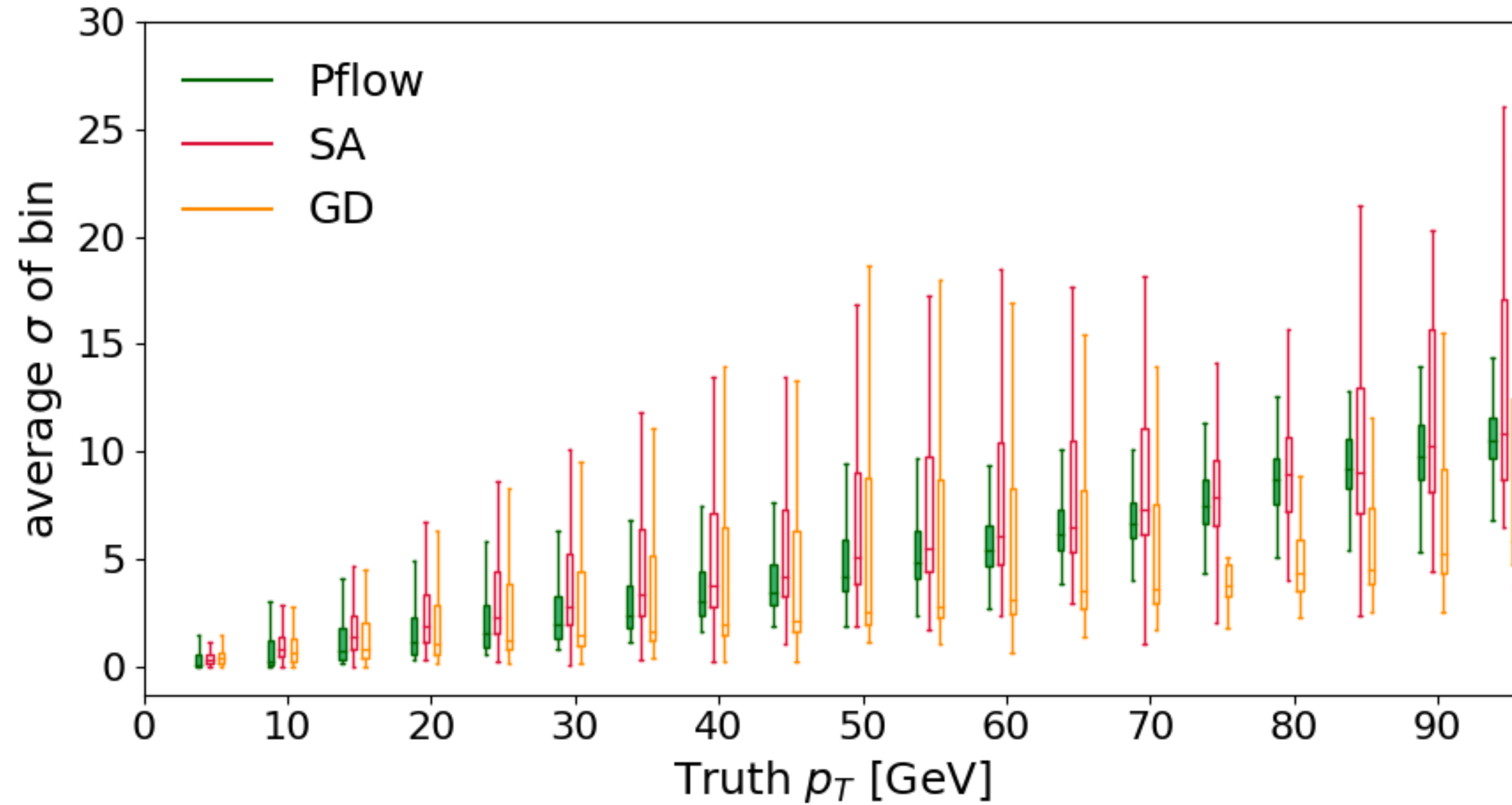
# Matching with truth



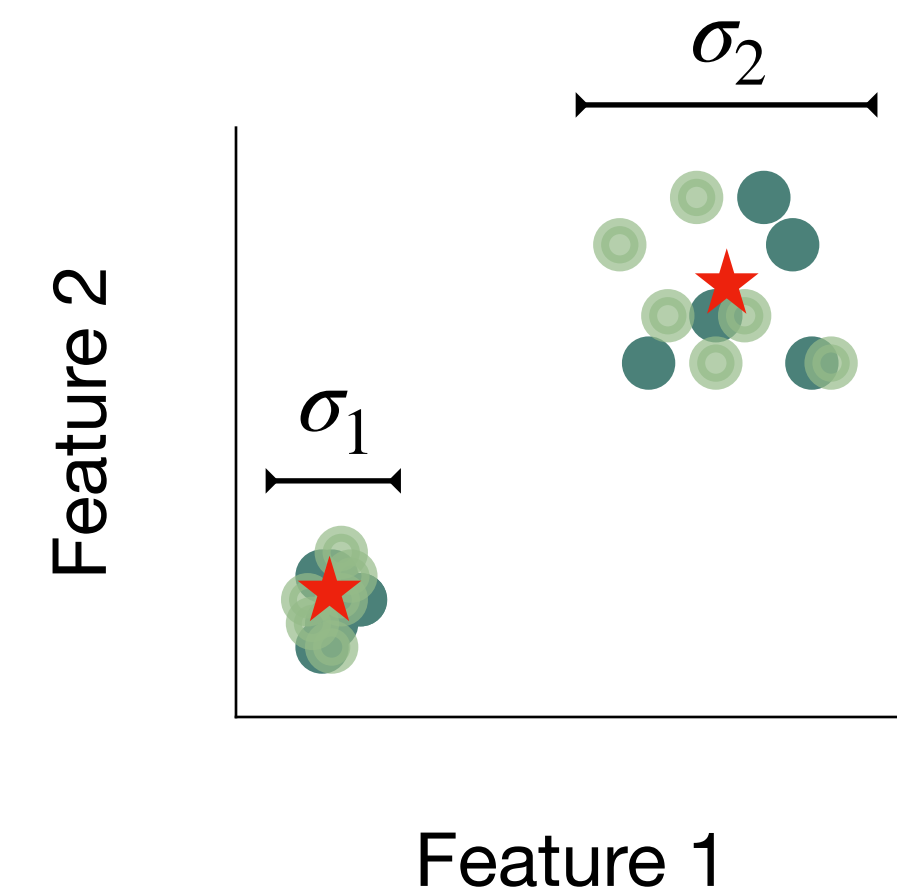
- Matching Cost — MSE of  $p_T, \eta, \phi$  + BCE of class
- SA — to high cost
- GD — good agreement



# Resolution

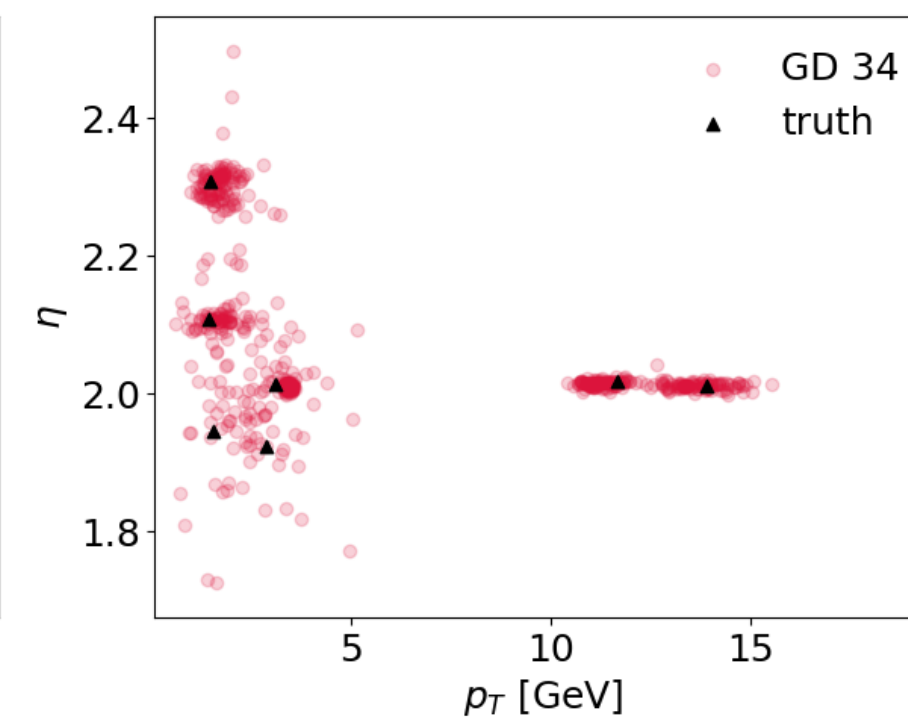
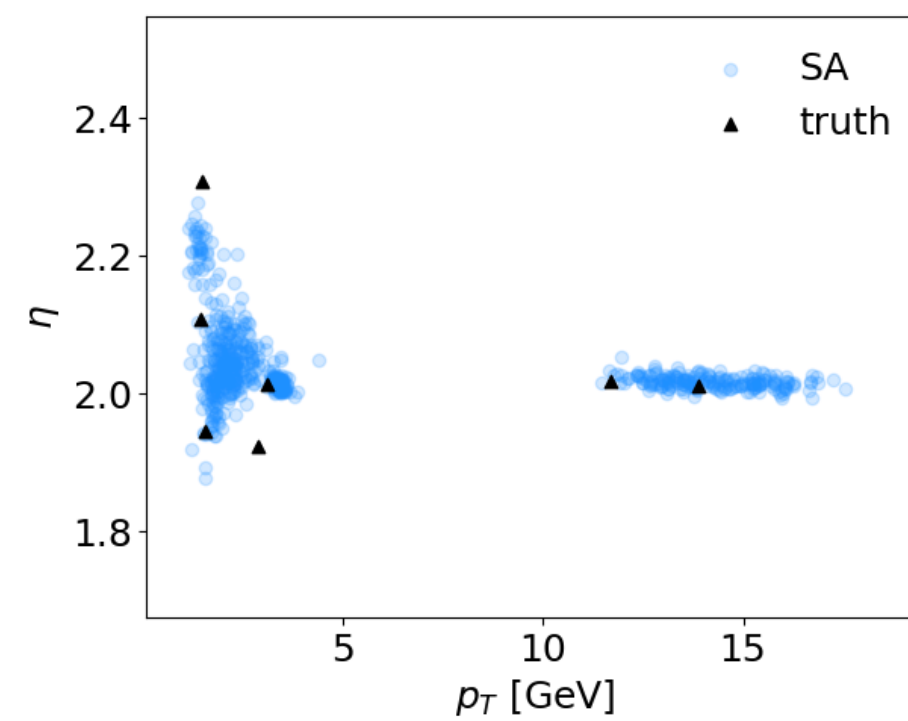
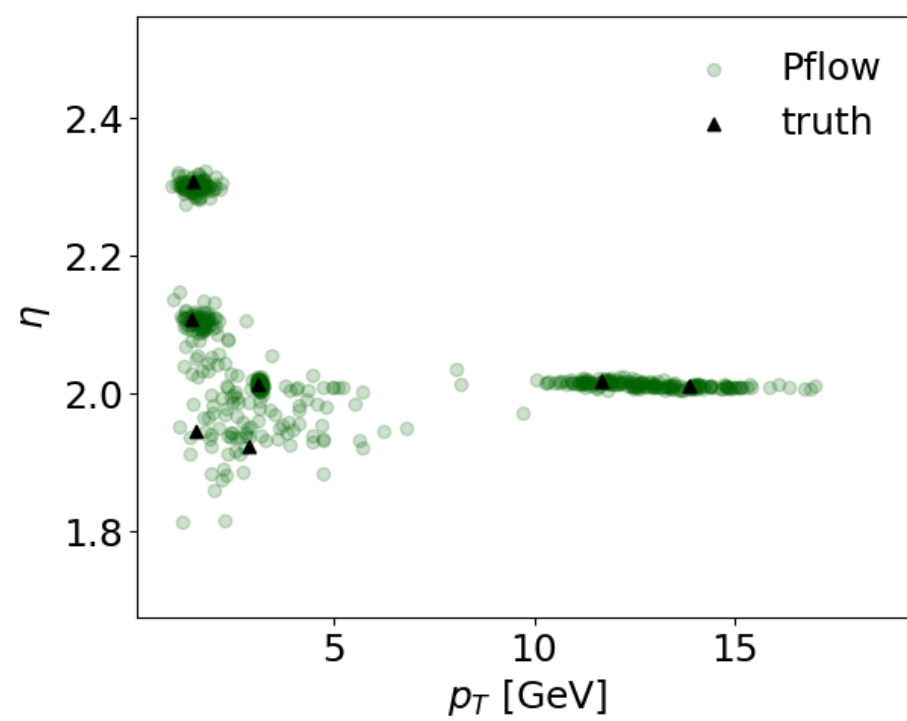
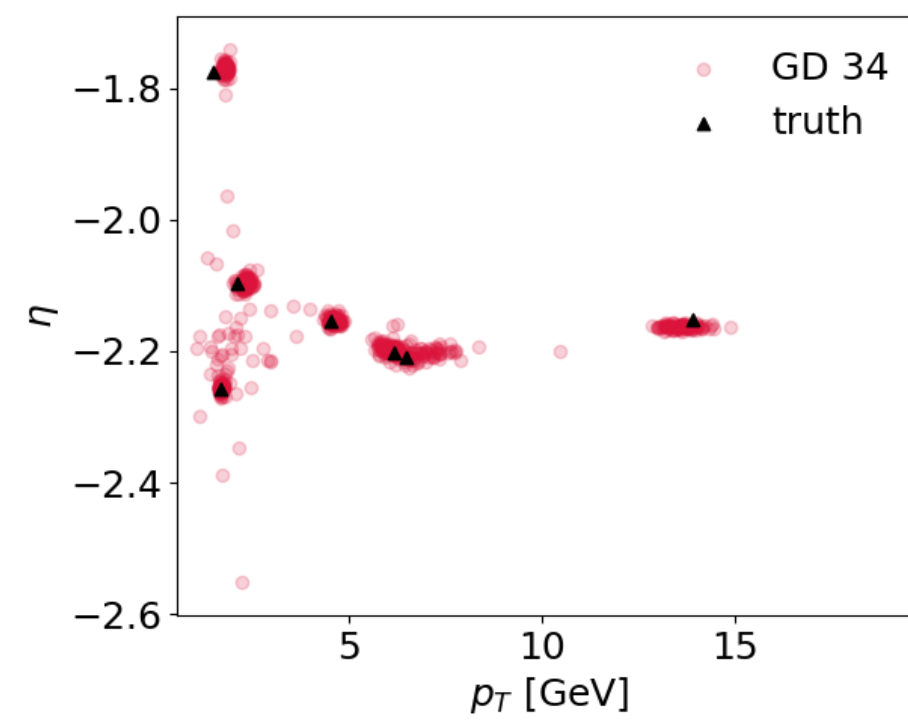
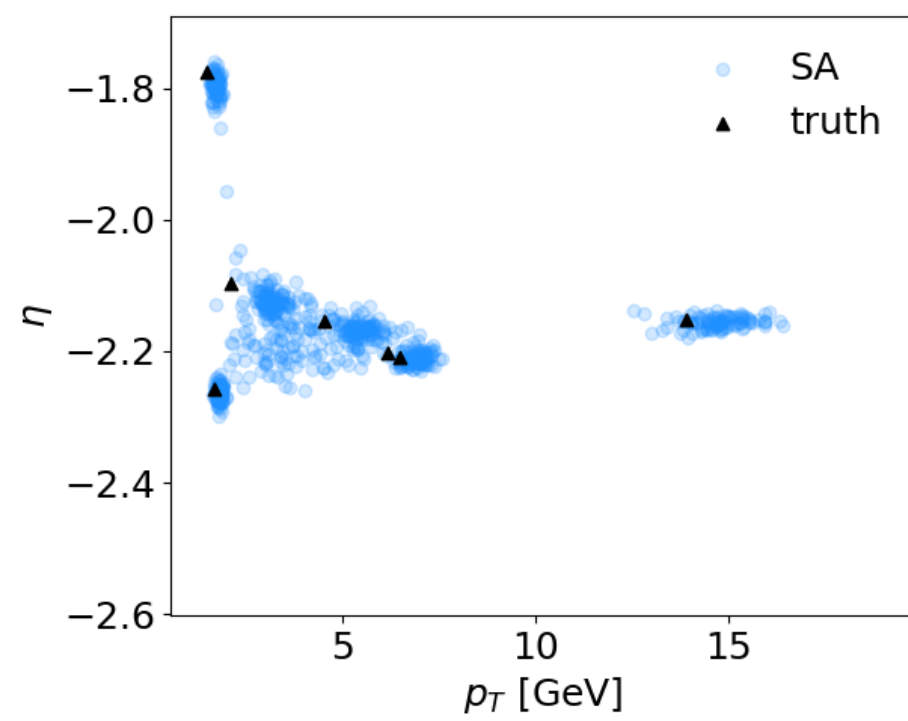
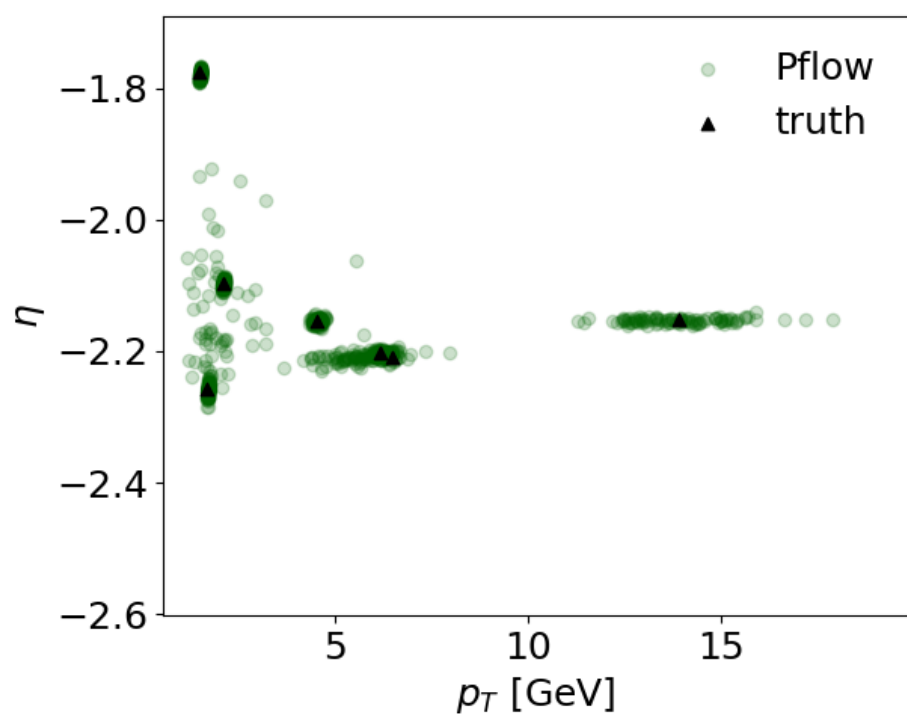
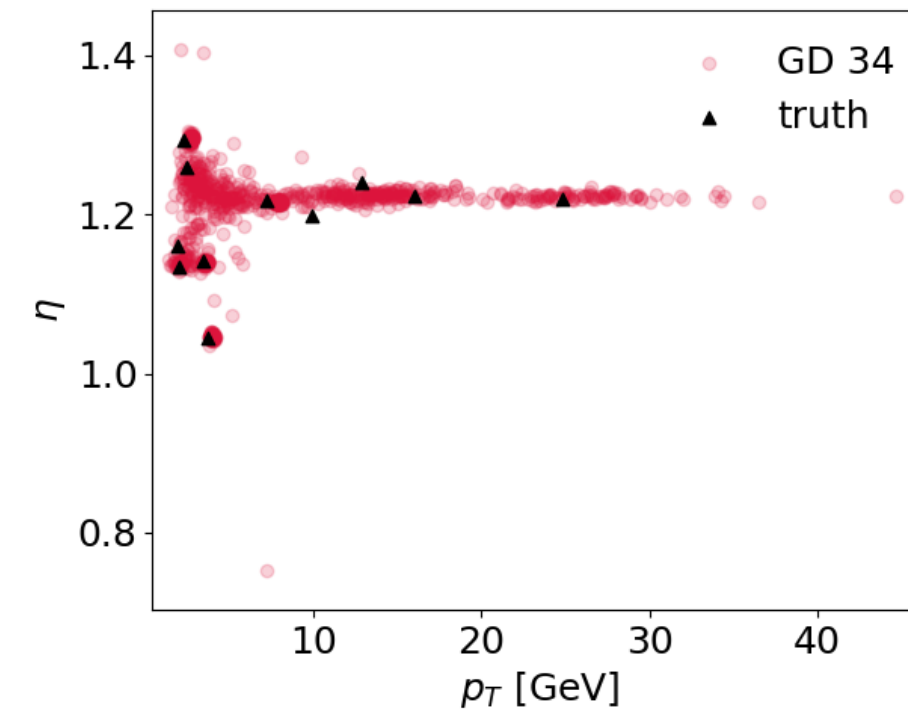
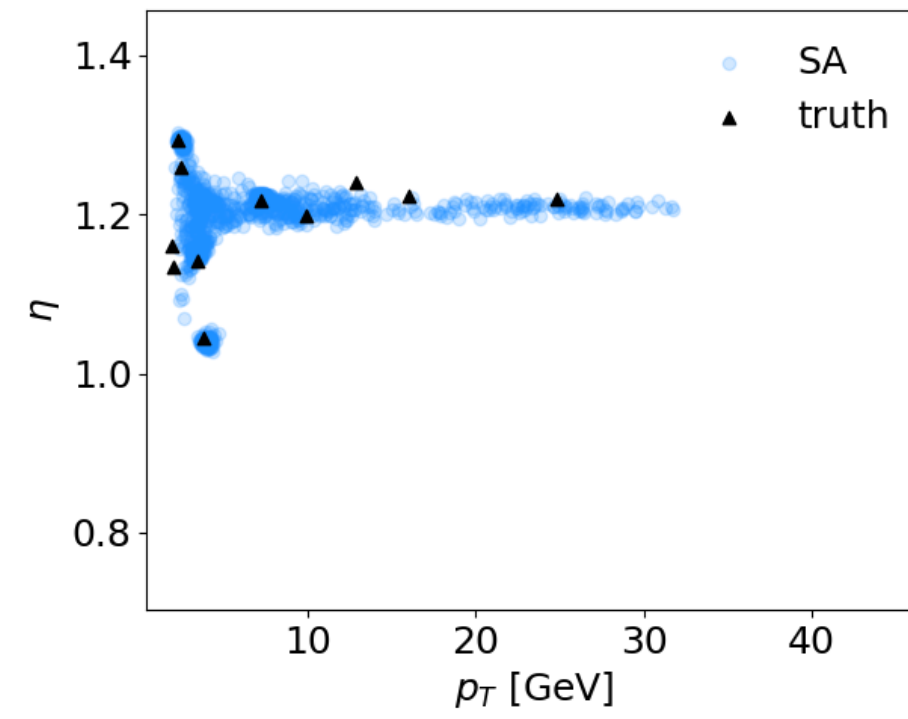
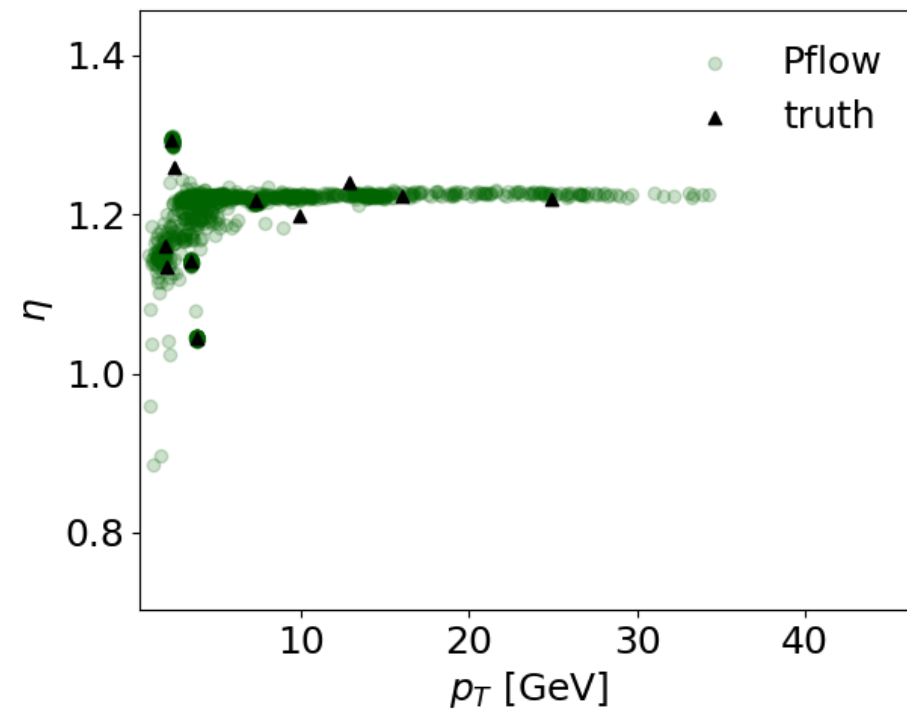


- For each truth particle take  $\sigma$  of all associated replicas
- Difficulties at high  $p_T$





# Event displays



# Summary

- 3 approaches for a conditional end-to-end generative model  
Slot-Attention, Graph Diffusion, Graph-to-Graph Translation
- Goal to reconstruct constituents and model detector resolution
- New models show significant improvement w.r.t. the original
- GGT trainings is in progress