Learning physics-aligned representations for anti-neutron reconstruction in EM calorimeter

Yangu Li (李彦谷)
University of Chinese Academy of Sciences

Quantum Computing and Machine Learning Workshop
August 18, 2026 arXiv: 2607.11139

University of Chinese Academy of Sciences

First of all...

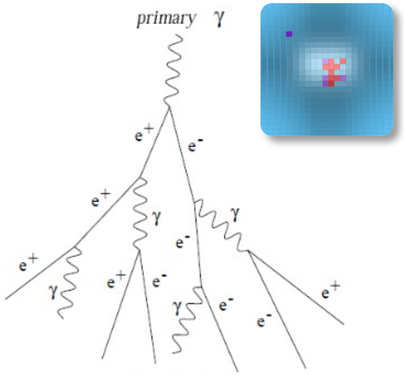
Why reconstruct hadrons in EM calorimeters
when dedicated hadronic calorimeters exist...?

The reason

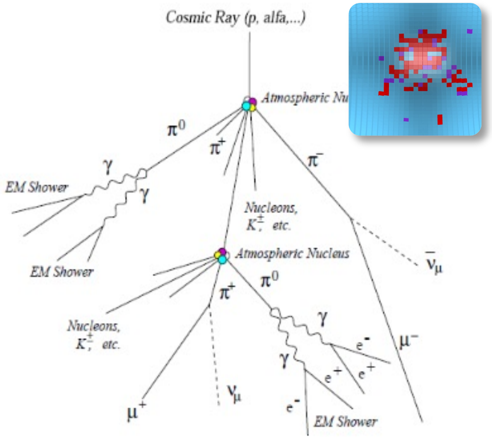
- **Calorimeters in HEP experiments have two types**
  - Electromagnetic type (ECAL) for detecting photons & electrons
  - Hadronic type (HCAL) for detecting neutral hadrons
  - Hardware & software optimized for different shower mechanisms

- **Many GeV-scale accelerator experiments only have ECAL**
  - Most e^+e^- colliders like BESIII, Belle II, STCF
  - Some heavy-ion & fixed-target experiments too

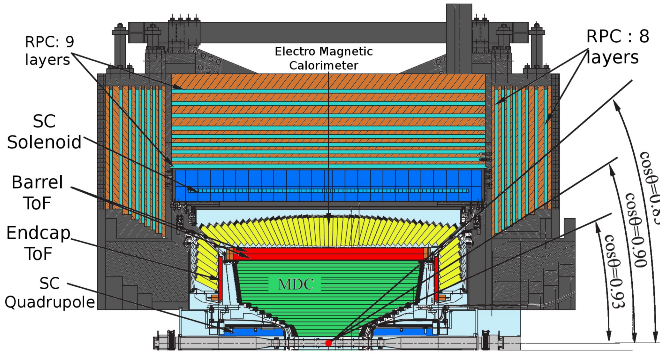
EM shower



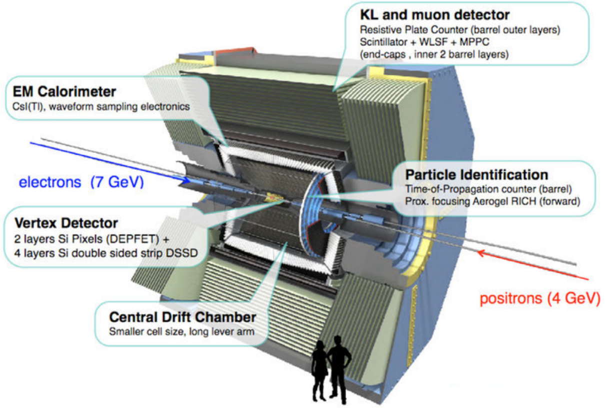
Hadronic shower



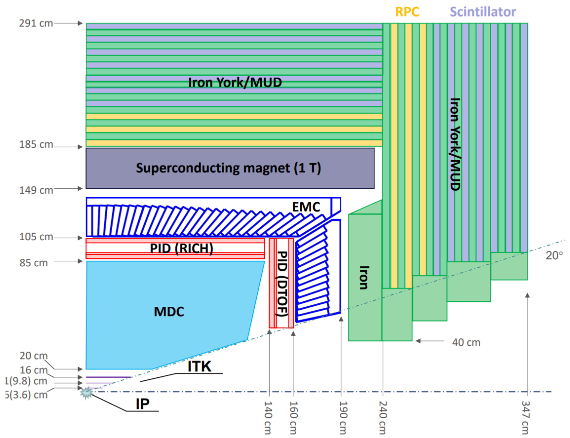
BESIII



Belle II



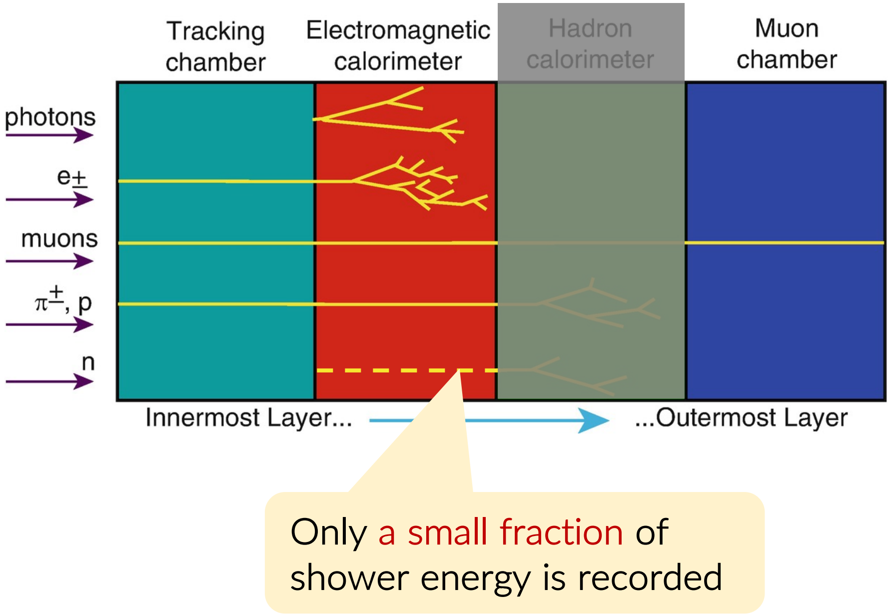
STCF 超级陶粲装置 Super Tau-Charm Facility



The issue

- **Direct reconstruction of neutral hadrons in ECAL is highly challenging**
  - Size & material hinder full containment of hadronic showers
  - Recorded energy deposits are weak, sparse, non-local

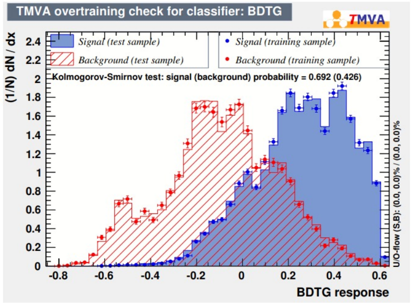
- **Conventional reconstruction methods are ineffective**
  - Momentum magnitude is unknown
    - Sizable energy leakage
  - Position is imprecise
    - Sparse & highly random hit clusters
  - Identification is not perfect
    - Can be confused with photon / beam background / detector noise
  - Simulation is biased
    - Lack of experimental calibration



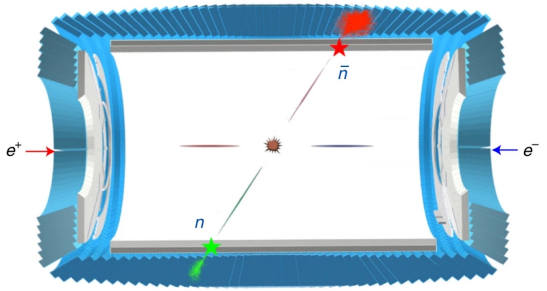
The payoff

- **Solving this issue has significant physics impact**
  - Neural hadrons are important probes for GeV-scale physics
    - Heavy-flavor physics
    - Light hadron spectroscopy
    - Exotic hadronic states etc.
  - And fundamental questions including CP violation, matter-antimatter asymmetry
  - Lifting this limitation expands the scientific reach of existing experiments

Study of $\Lambda \to n\gamma$ at BESIII
PRL **129**, 212002 (2022)



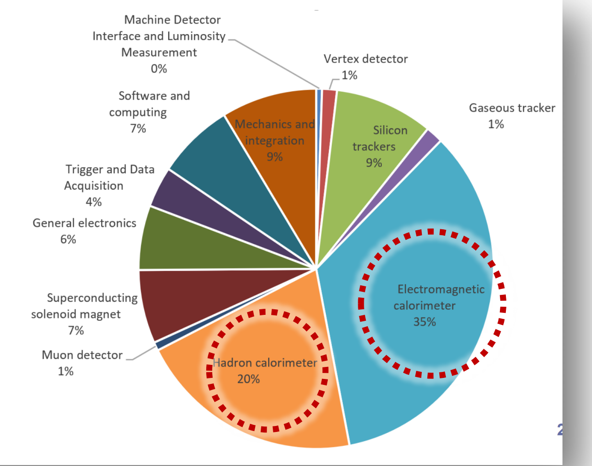
Study of $e^+e^- \to n\bar{n}$ at BESIII
Nature Phys. **17**, 1200-1204 (2021)



- **... and economic benefits**
  - ECAL is usually the most expensive component in a particle detector
    - HCAL is often the second
  - Making fuller use of ECAL, reduce the need for HCAL

CEPC reference detector

系统	造价（万元）	比例
探测器与加速器结合部和亮度测量	1,403	0.5%
顶点探测器	3,599	1.3%
硅径迹探测器	23,756	8.9%
气体径迹探测器	4,943	1.9%
电磁量能器	91,974	34.5%
强子量能器	54,613	20.5%
缪子探测器	2,020	0.8%
探测器磁体	17,573	6.6%
电子学系统	15,417	5.8%
触发与数据获取系统	9,741	3.7%
软件与计算系统	18,480	6.9%
探测器总体机械与安装	23,095	8.7%
合计	**266,620**	**100.0%**

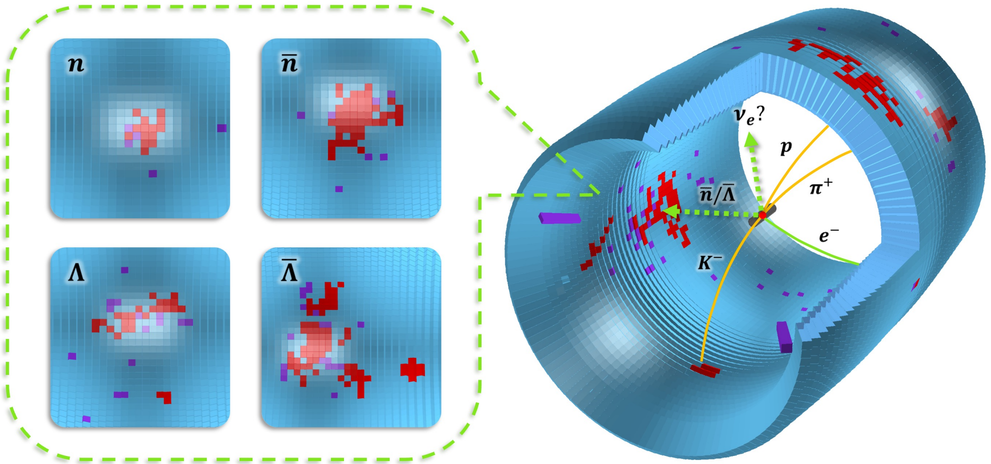


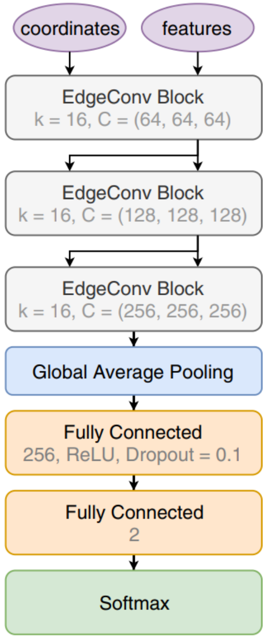
The ML solution

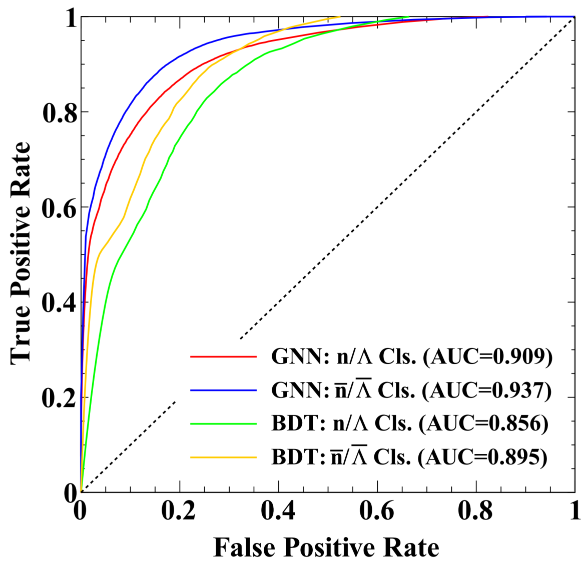
- **Learn representations of neutral-hadron energy deposition patterns in ECAL**
- **Use neural networks to infer neutral hadron properties**
  - e.g., particle type, momentum direction, momentum magnitude

Our first attempt (I)

- **Neutron identification with Graph Neural Networks**
  - Inspired by ParticleNet for jet tagging @ LHC
  - Represent ECAL energy deposits as a point cloud
  - Distinguish single-neutron patterns from photon-accompanied ones (e.g., $\Lambda \to n\pi^0$)

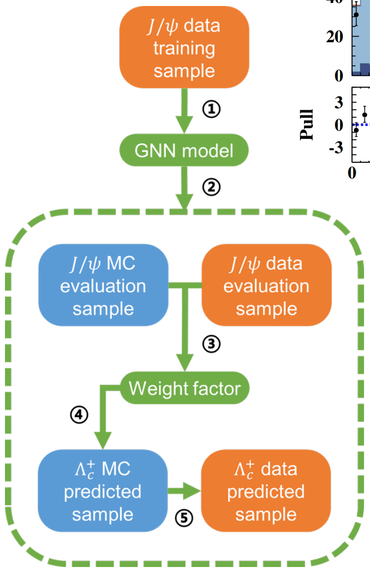


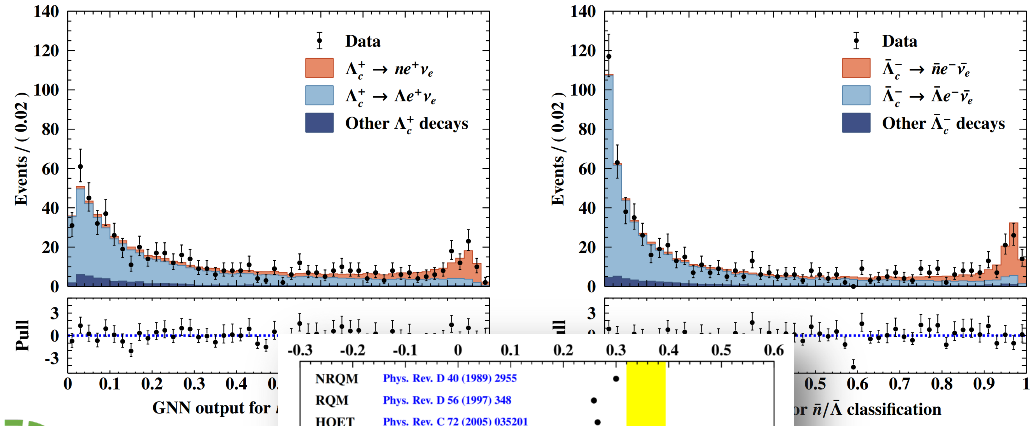


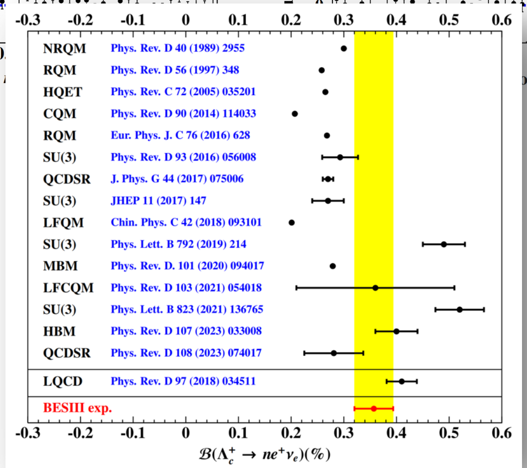


Our first attempt (II)

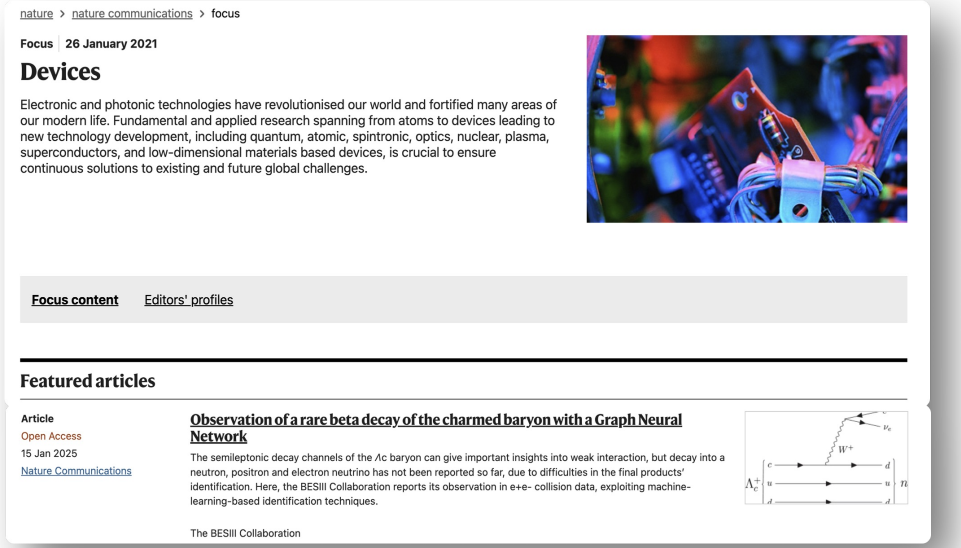
- **Applied to BESIII physics analysis**
  - Enable first observation of charmed baryon decay $\Lambda_c^+ \to n e^+ \nu_e$
  - Significance improved from $< 3\sigma$ to $> 10\sigma$, facilitating examination for many theoretical models
  - Use data-driven methods for model calibration & uncertainty quantification





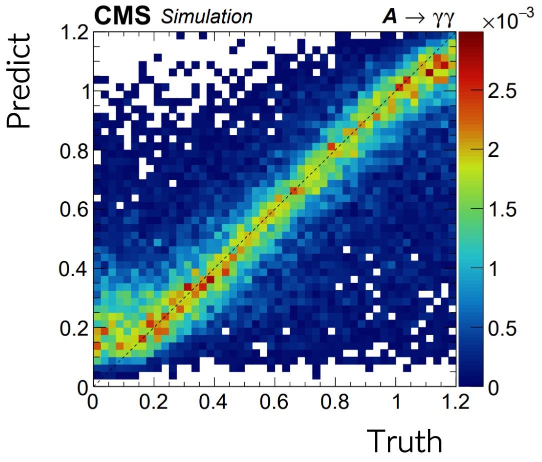


Nature Commun. **16**, 681 (2025)
Selected as Editors' Highlight

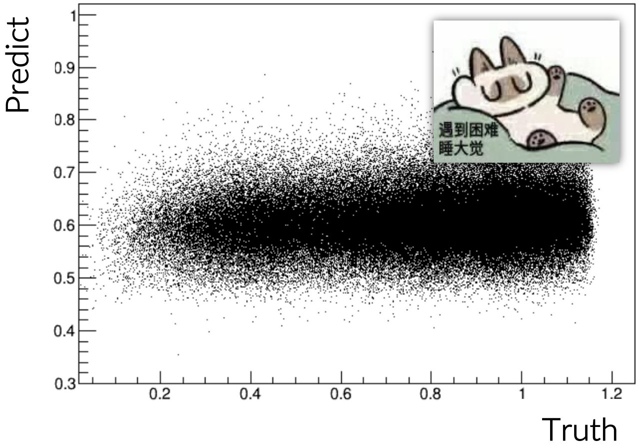


Moving forward

- **Full kinematic reconstruction is desired beyond identification**
  - Momentum information is essential for precise measurements
  - Point-cloud model fail to learn stable momentum mapping



Ideal behavior:
Positively correlated mapping



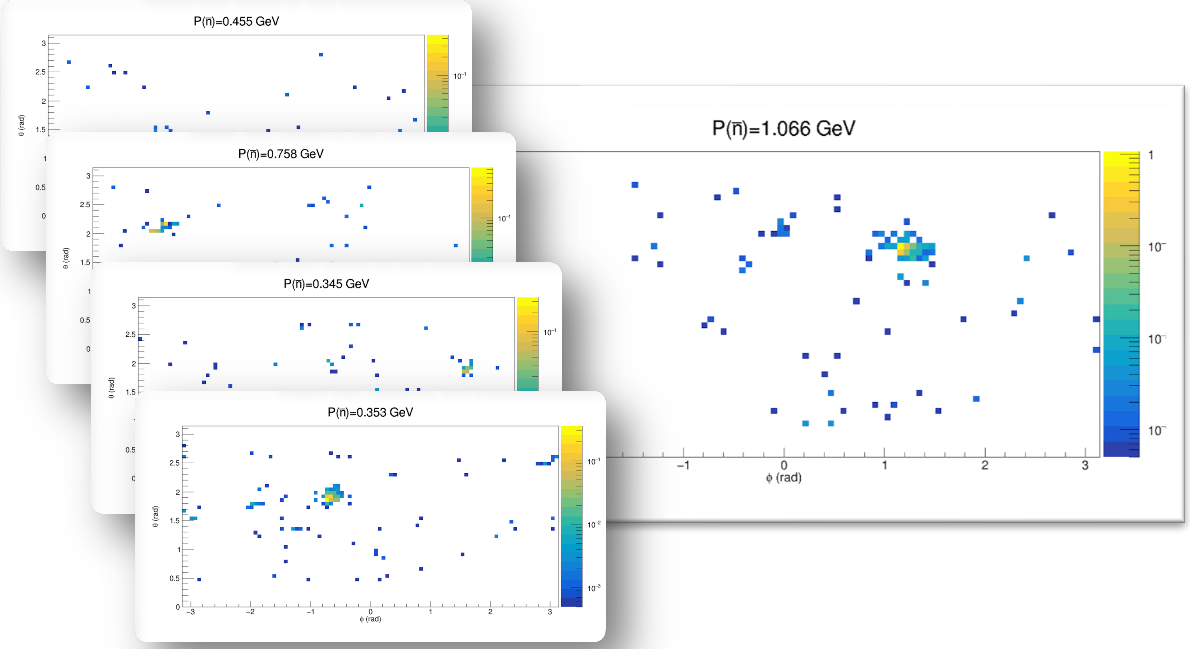
GNN result:
Predictions collapse toward the mean, yielding a local minimum of the loss

New representations & networks should be designed;
What clues can guide them?

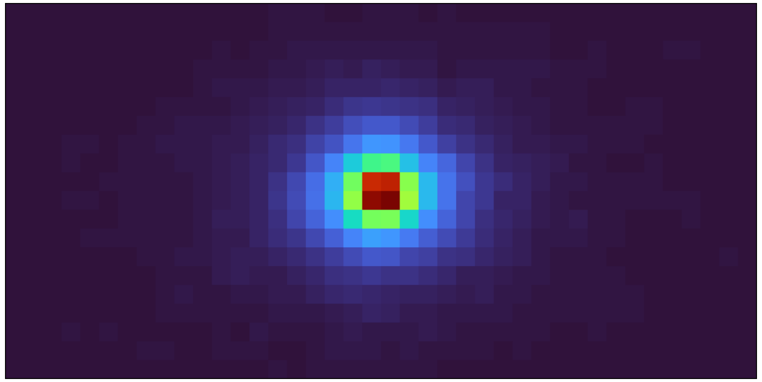
Clues I: physics priors in data patterns

- **At single-event level:**
  - Sparse (~3% of ECAL cells are activated)
  - Highly stochastic & non-local

- **At event-averaged level:**
  - Central concentration around incident point
  - Radial, diffusion-like attenuation

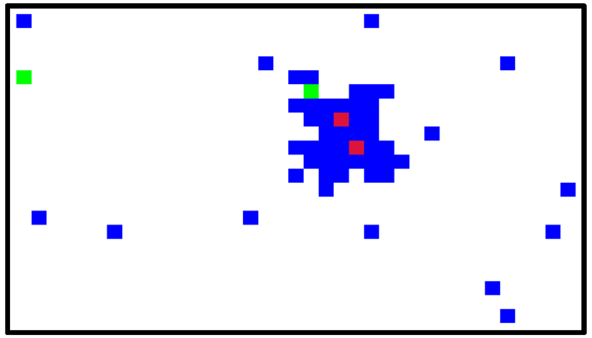


Mean



Direct consequences of hadronic shower mechanism;
difficult to calculate analytically,
but can be used as priors in model design

Clues II: tradeoffs among representations



$E = 5.37\text{e}-4\ \text{GeV}, \phi = -51.01°, \theta = 20.93°$

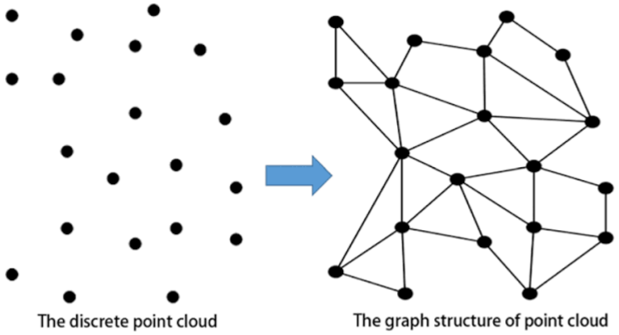
$E = 2.11\text{e}-2\ \text{GeV}, \phi = -13.53°, \theta = 88.45°$

$E = 9.85\text{e}-1\ \text{GeV}, \phi = 7.55°, \theta = 100.81°$

$\vdots$

$E = 1.18\text{e}-3\ \text{GeV}, \phi = 67.57°, \theta = 35.24°$

$E = 7.21\text{e}-4\ \text{GeV}, \phi = -1.59°, \theta = 144.76°$



Image

- ✓ Intuitive
- ✓ Capture local spatial context
- ✗ Projection compresses high-dimensional features
- ✗ Low computational efficiency for sparse images

Sequence

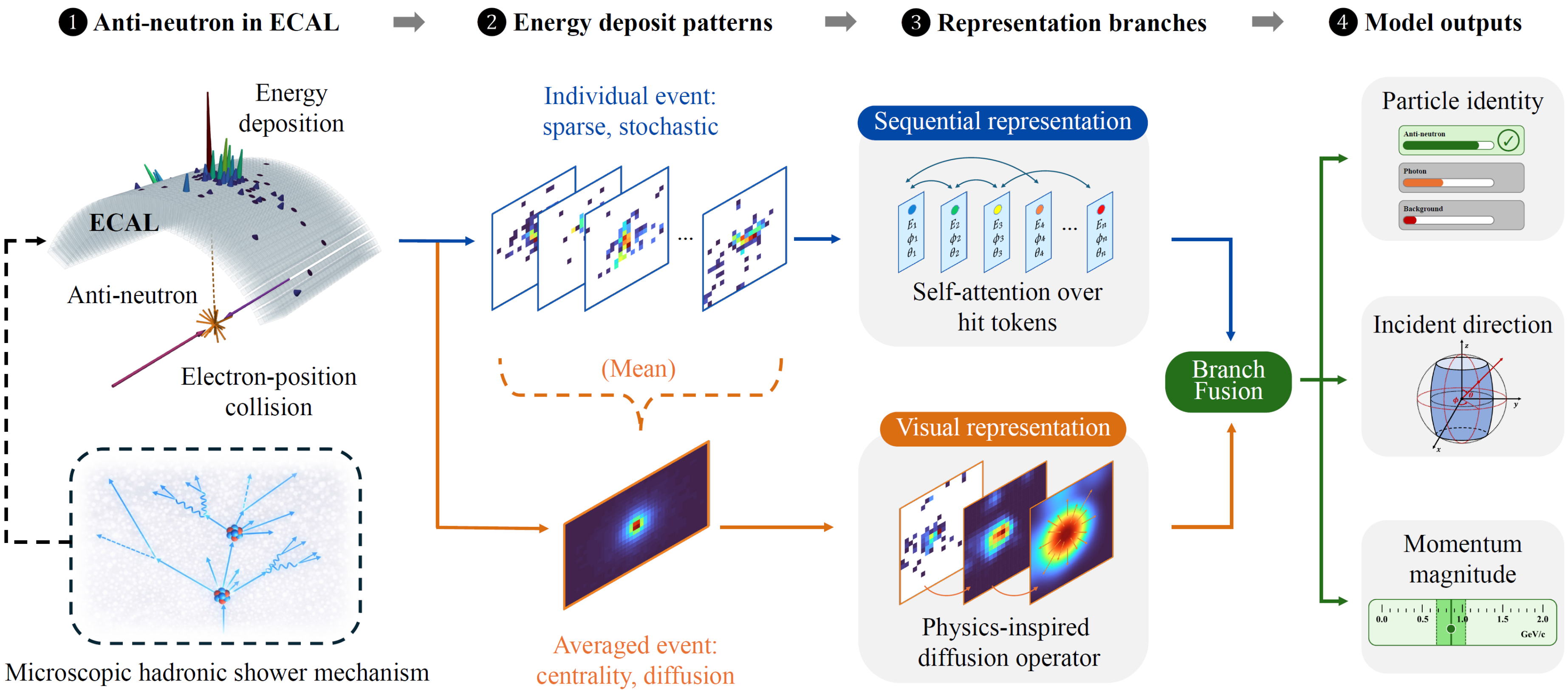
- ✓ High information density
- ✓ Capture long-range correlations
- ✗ Require imposed ordering

Graph / point cloud

- ✓ Retain complete high-dimensional information
- ✓ Order-invariant
- ✗ Difficult to scale up

Combine multiple representations in a single model to
leverage their complementary strengths

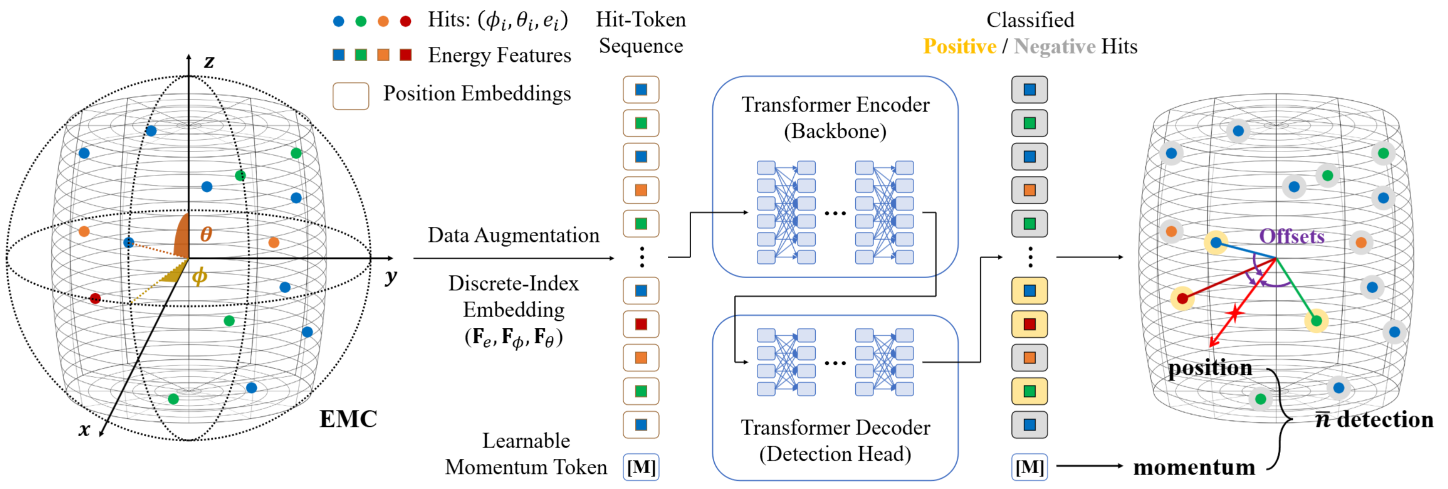
Mixed-representation Calorimetric Network

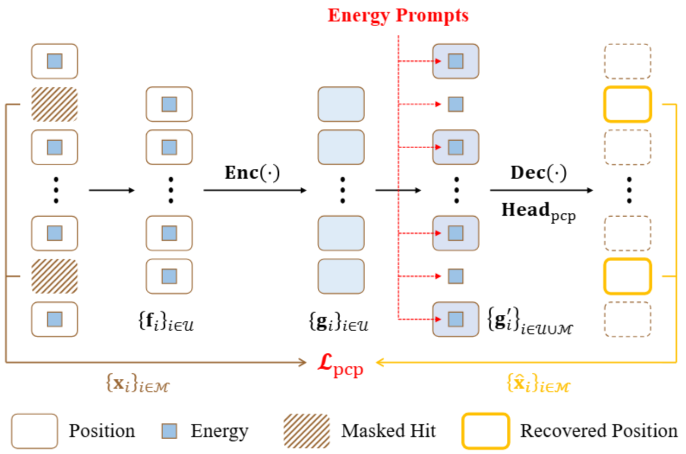


- A sequential branch aggregates dispersed hit tokens
- A visual branch encodes the averaged spatial prior using a diffusion operator
- The fused representations jointly reconstruct particle properties

Sequential representation branch

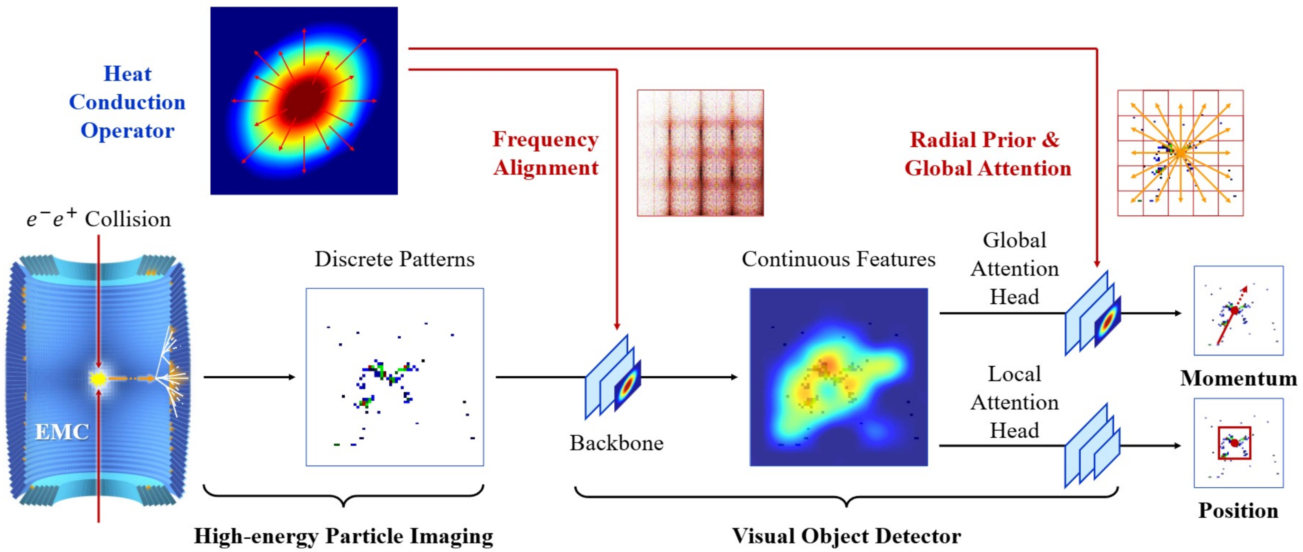
- **Input:** hit-token sequence containing (E, ϕ, θ) features + learnable momentum token
  - Data augmentation to mitigate sorting order
- **Network:** Transformer encoder & decoder
- **Outputs:** internal voting for incident position and momentum
- **Pretraining:** position-cloze learning with informative hit tokens masked

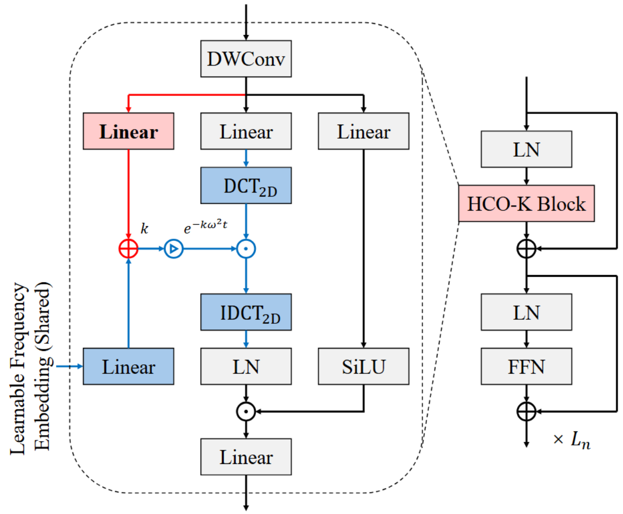




Visual representation branch

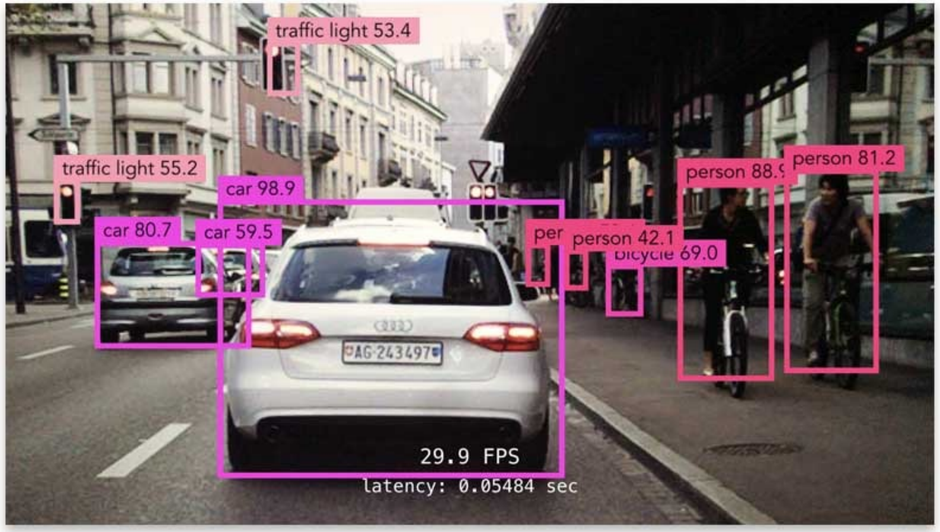
- **Input:** (ϕ, θ) projection image
  - Map log-scaled energy to RGB channels
- **Network:** visual object detector
  - RetinaNet with a feature pyramid
  - Add a physics-inspired diffusion operator to encode centrality and radial attenuation
- **Outputs:** pseudo bounding boxes around incident point





Branch fusion

- **Objection-detection style outputs**
  - A list of neutral-hadron candidates
  - Ranked by a confidence score
  - Each with particle type, position, momentum



More flexible than event-level classification/regression in real experimental scenarios

- **Fusion of visual & sequential branches**
  - Independent candidate lists from two branches
  - Calibrate confidence scores
  - Match candidate pairs according to angular separation and confidence
  - Fuse position & momentum estimates using confidence-based weights
  - Retain unmatched pairs

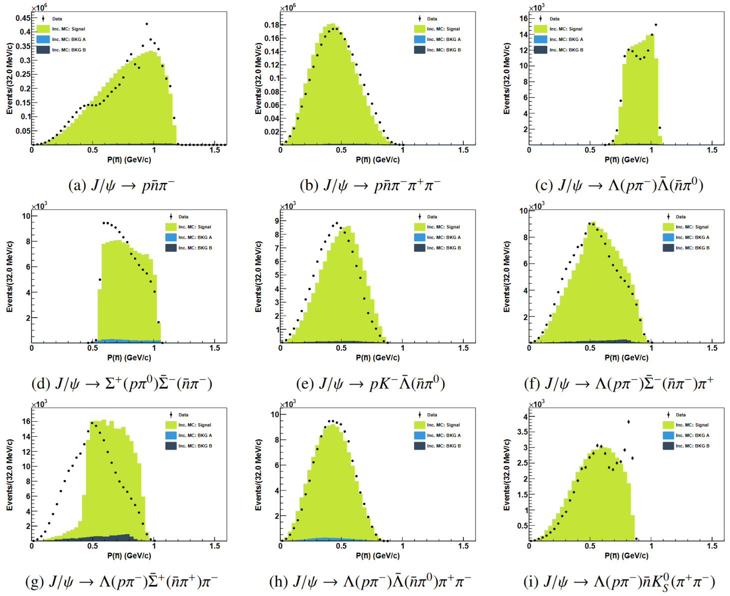
Real-data benchmark

- **Importance**
  - Geant4-based simulation is known to be biased
  - Prove the robustness of network under complex experimental conditions

- **Large & diverse anti-neutron sample from BESIII**
  - 3 energy points, 36 decay channels, 5.3M events
  - Broad kinematic coverage and diverse background environments
  - Truth labels inferred from reconstructed recoil system

Take anti-neutron as the starting point: annihilation produces comparatively large energy deposits

		$p\bar{n}\pi^-$	$p\bar{n}\pi^-\pi^+\pi^-$	$\Lambda\bar{\Lambda}$	$\Sigma^+\bar{\Sigma}^-$	$pK^-\bar{\Lambda}$	$\Lambda\bar{\Sigma}^-\pi^+$	$\Lambda\bar{\Sigma}^+\pi^-$	$\Lambda\bar{\Lambda}\pi^+\pi^-$	$\Lambda\bar{n}K_S^0$
J/ψ decays	ML	1,000,000	1,101,047[3]	125,552	104,682	114,403	168,332	333,535	130,475	68,292
	Physics	100,000	100,000	100,000	100,000	100,000	100,000	100,000	100,000	20,000
$\psi(2S)$ direct decays	ML	95,665[4]	485,279	-	-	-	-	-	10,124	-
	Physics	-	100,000	6,373	6,597	-	-	-	10,000	2,932
$\psi(2S)$ cascade decays	ML	-	91,665	5,436	4,213	4,844	-	-	-	-
	Physics	100,000	10,000	5,000	5,000	5,000	5,484	5,980	4,524	4,486
e^+e^- annihilation @3.773 GeV	ML	81,730	137,306	-	-	-	-	-	-	-
	Physics	-	-	-	-	3,623	1,415	1,633	1,227	1,614



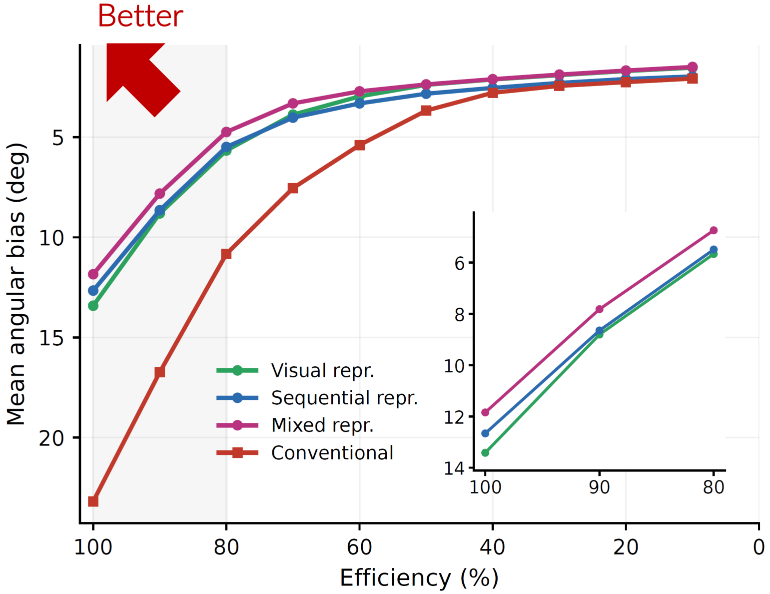
(a) $J/\psi \to p\bar{n}\pi^-$ (b) $J/\psi \to p\bar{n}\pi^-\pi^+\pi^-$ (c) $J/\psi \to \Lambda(p\pi^-)\bar{\Lambda}(\bar{n}\pi^0)$

(d) $J/\psi \to \Sigma^+(p\pi^0)\bar{\Sigma}^-(\bar{n}\pi^-)$ (e) $J/\psi \to pK^-\bar{\Lambda}(\bar{n}\pi^0)$ (f) $J/\psi \to \Lambda(p\pi^-)\bar{\Sigma}^-(\bar{n}\pi^-)\pi^+$

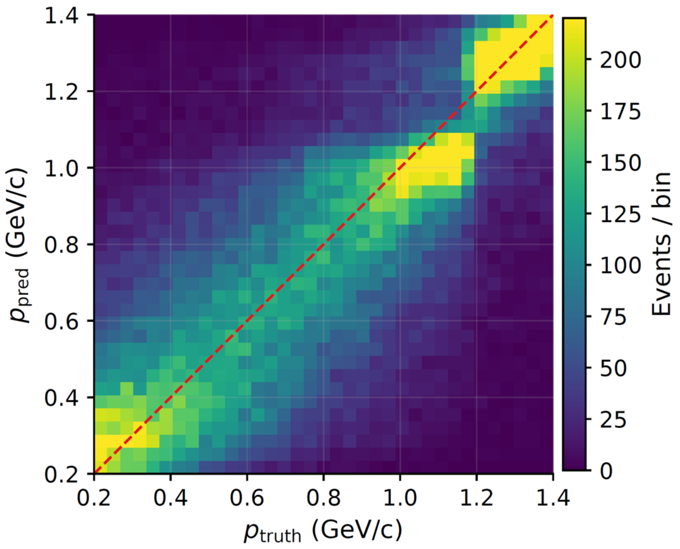
(g) $J/\psi \to \Lambda(p\pi^-)\bar{\Sigma}^+(\bar{n}\pi^+)\pi^-$ (h) $J/\psi \to \Lambda(p\pi^-)\bar{\Lambda}(\bar{n}\pi^0)\pi^+\pi^-$ (i) $J/\psi \to \Lambda(p\pi^-)\bar{n}K_S^0(\pi^+\pi^-)$

Single-particle reconstruction

- **Directional precision nearly doubles from conventional method**
  - Mean angular bias decreases from 23.2° to $11.8°$, corresponding to 96% precision improvement
  - Advantage persists across the efficiency range
  - Mixed representation outperforms either branch alone

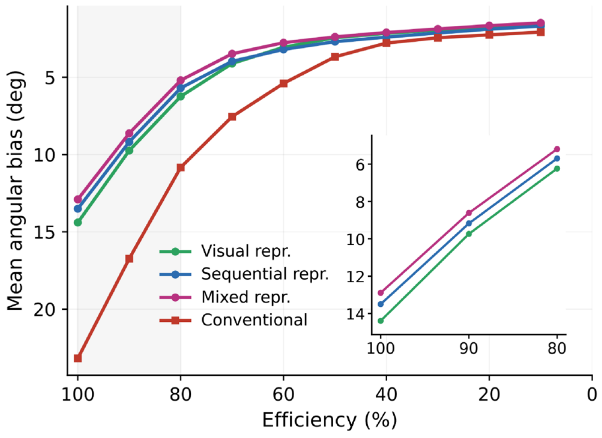


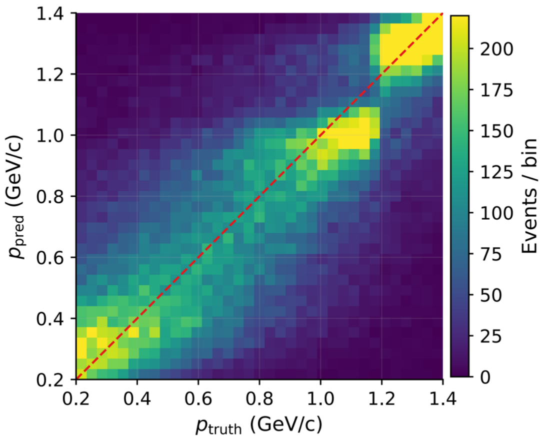
- **Achieve direct momentum measurement for the first time**
  - Nearly linear & unbiased predictions over broad momentum region
  - Momentum resolution reaches 17.6% @ $1\ \mathrm{GeV}/c$
    - Dedicated HCALs at LHC typically $\sim 50\%/\sqrt{E}$



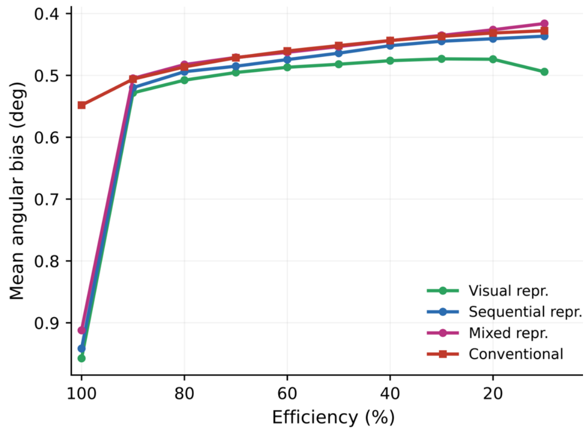
Multi-particle reconstruction

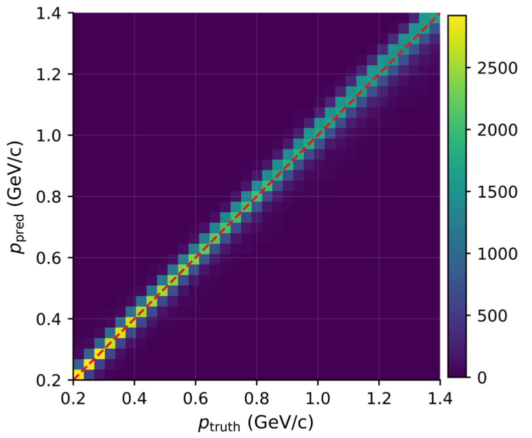
Anti-neutron



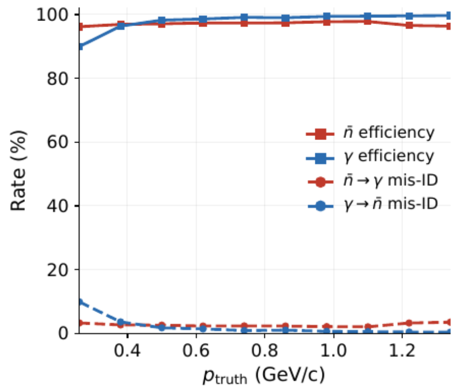


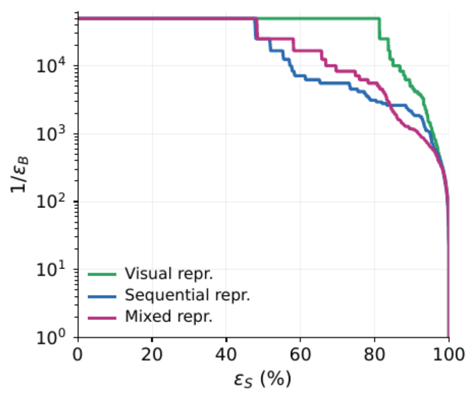
Photon





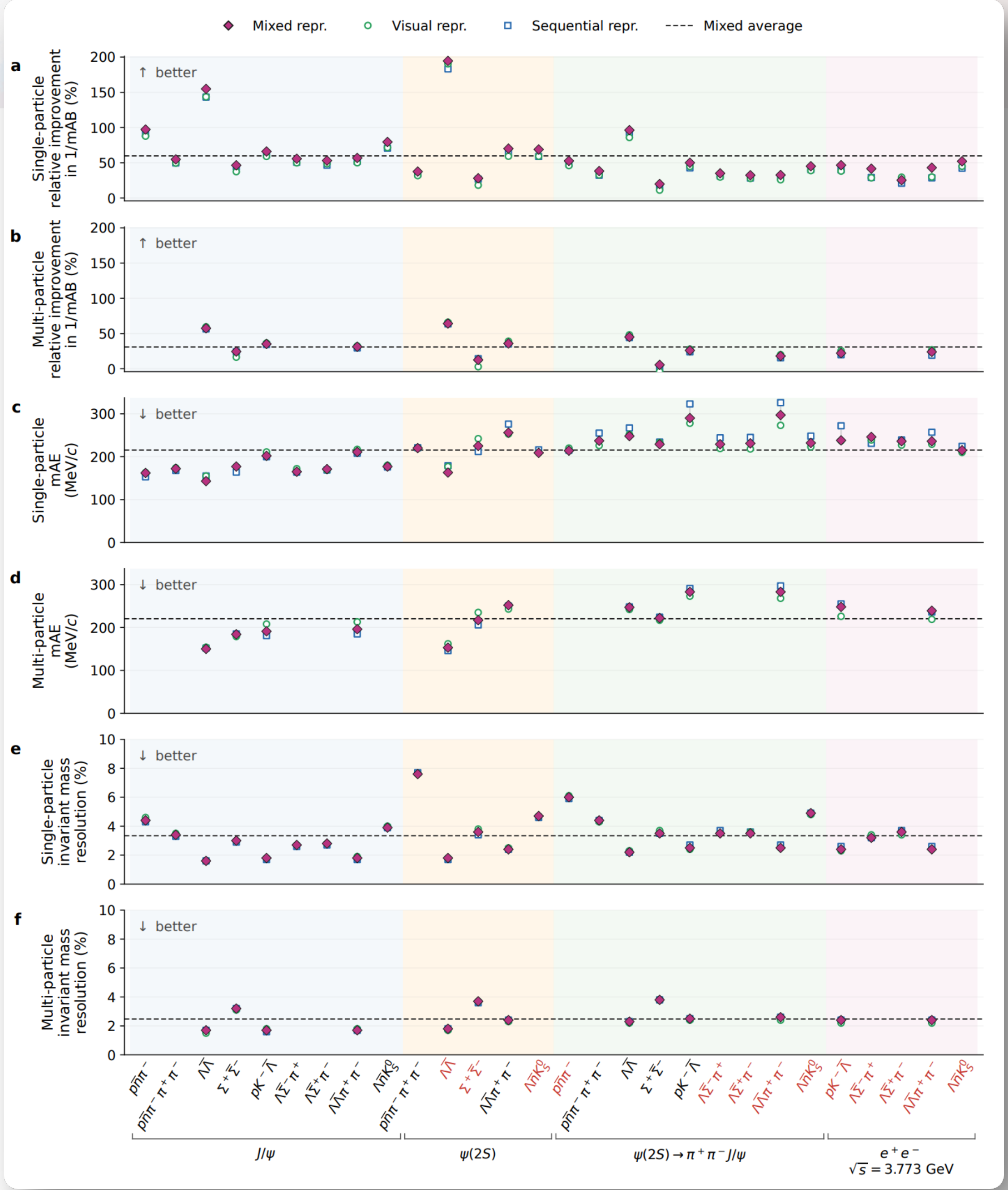
- **In a more complex & realistic environment**
  - Simultaneous reconstruction for anti-neutron & photon
  - Anti-neutron performance remains stable
  - Photon performance remains competitive
  - Support particle-level identification & event-level classification





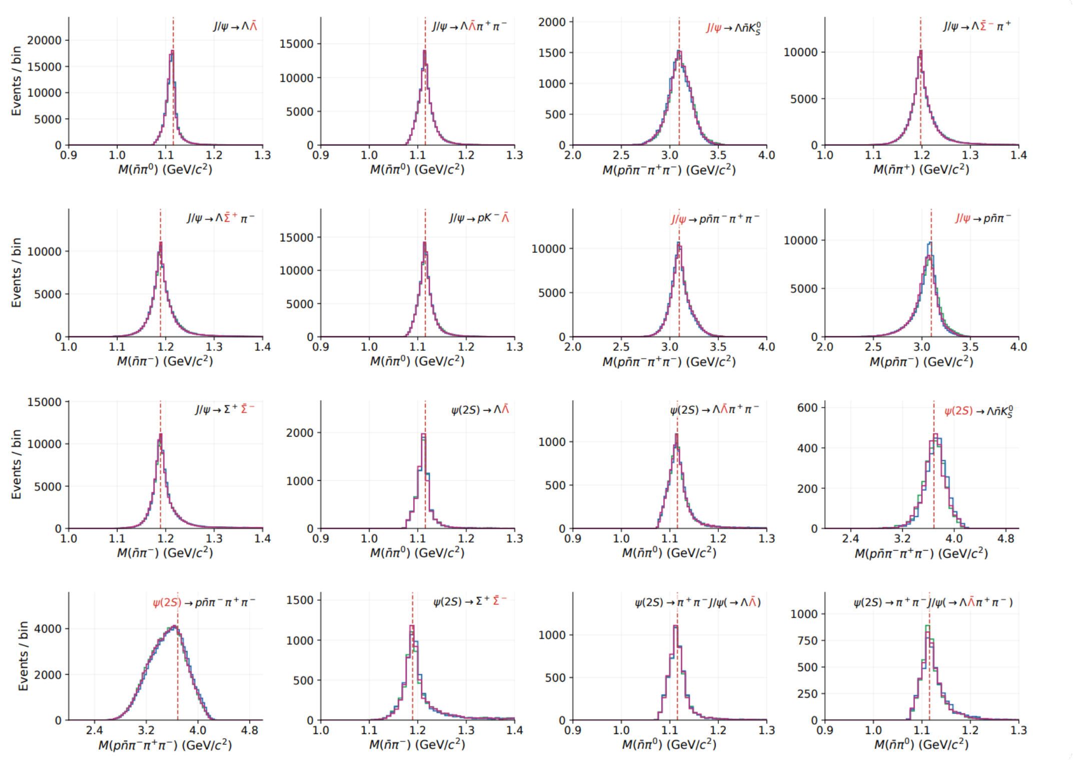
Generalization ability

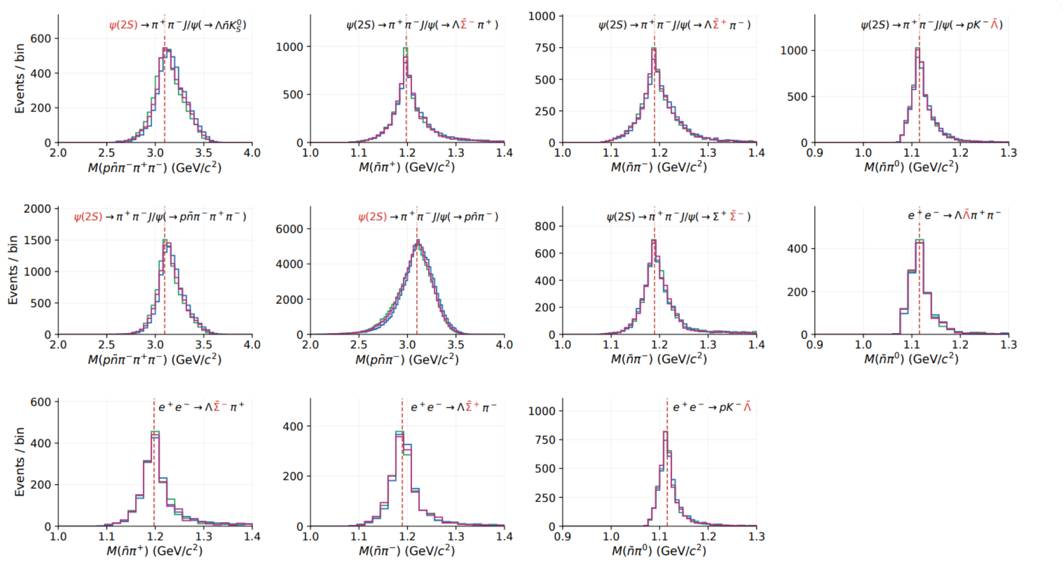
- **Extensive tests across 28 benchmark channels**
  - Includes 13 channels held out from training
  - Performance consistently retained across the benchmark
  - e.g., improvements in directional precision are 194.5% in maximum, 19.8% in minimum, 59.8% in average



Application to physics analysis

- **Reconstruct resonances decaying to anti-neutron**
  - $\bar{\Lambda} \to \bar{n}\pi^0, \bar{\Sigma}^+ \to \bar{n}\pi^+, \bar{\Sigma}^- \to \bar{n}\pi^-, J/\psi \to p\bar{n}\pi^-$, etc.
  - Combine model-predicted anti-neutron 4-momentum with standard reconstructions for remaining particles
  - Obtain invariant mass peaks with unbiased centroids and well-controlled widths
    - Averaged mass resolution ~3%





Summary

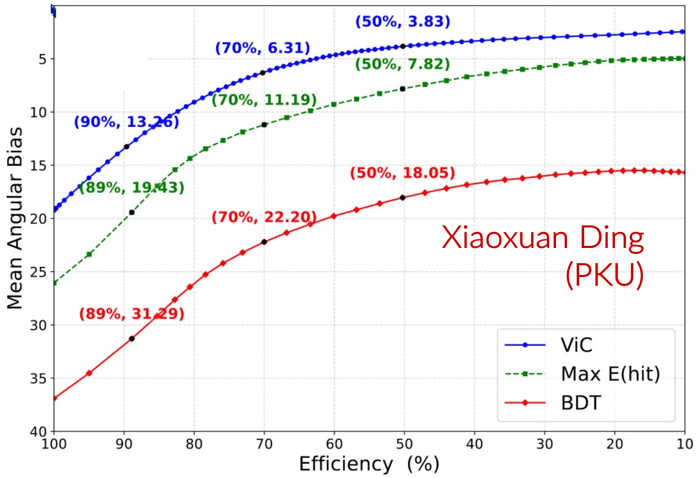
- **Neutral hadron reconstruction in ECALs is a long-standing issue in GeV-scale experiments**
  - Detector hardware was not designed/optimized for this task
  - Machine learning can substantially mitigate this limitation

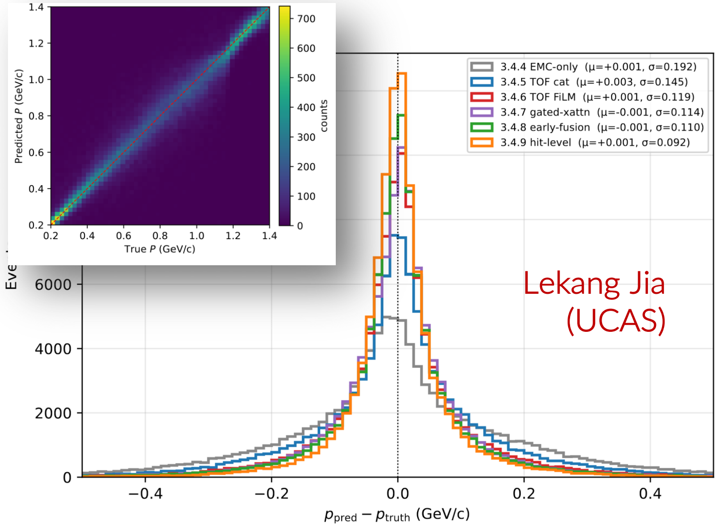
- **We develop a physics-aligned mixed-representation network**
  - A sequential branch aggregates dispersed energy deposits
  - A visual branch encodes averaged spatial prior using a diffusion operator

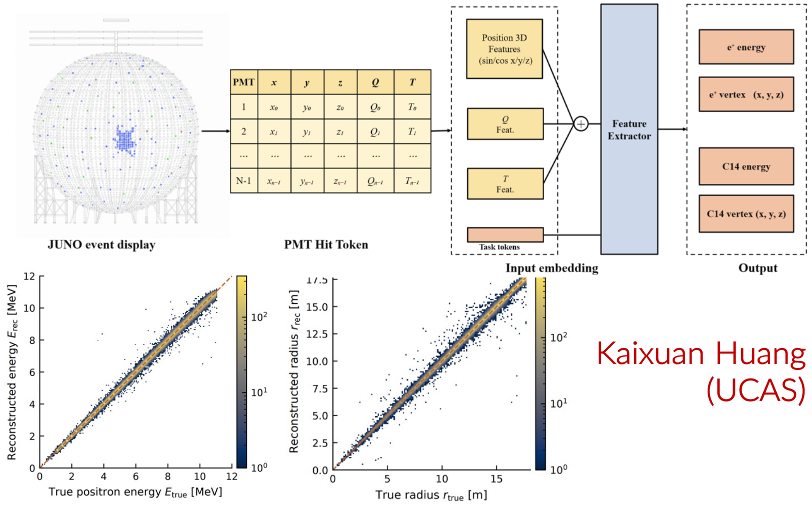
- **Model is extensively evaluated on real-data benchmarks**
  - Directional precision improved by up to 96%
  - Realize momentum measurement capability for the first time
  - Robust performance retained under complex experimental conditions

Outlook (I)

- **An expandable framework for end-to-end particle reconstruction**
  - To more neutral particles: neutron, K_L^0 meson, …
  - To more detectors: time-of-flight detector, muon counter, …
  - To more experiment settings: other flavor facilities, …, neutrino & astroparticle experiments with similar data patterns







Same framework is effective for K_L^0 reconstruction

Adding TOF information can greatly improve momentum prediction

Proposal to migrate the framework for JUNO neutrino reconstruction

Outlook (II)

- **Implications for running experiments like BESIII**
  - Purely offline algorithm, no need for hardware upgrade or operation interruption
  - Expand the scientific reach at negligible cost
  - Some physics analyses are ongoing

- **A new direction for future detector design**
  - Hardware limitations can be mitigated by AI-powered software
  - Why not jointly optimize hardware & software in an AI-native framework?
  - e.g., a more capable yet less expensive calorimeter that reconstructs both EM and hadronic showers...

Thanks for your attention!