EuCAIFCon 2024

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Anomaly detection search for BSM physics in ATLAS experiment at LHC

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WHERE IS LHC GOING?

Finding anomalies in Jets

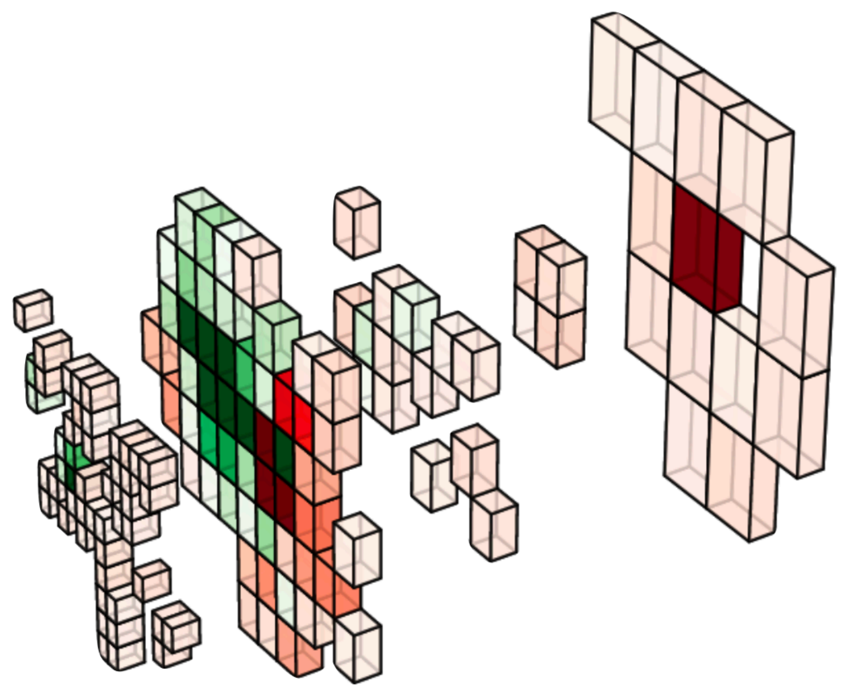
- No Physics Beyond Standard Model (BSM) has been observed at the LHC (yet!)

- The currently most used search paradigm is using model-dependent approaches
  ↪What if these models have blind spots for unconventional new physics signatures?
  ↪If there's new Physics in the current LHC data we can't miss it!

- Anomaly detection can find deviations in Standard Model events, without any signal dependency

Use jets as tools!

- Searches in full hadronic final states
  ↪Investigate its substructure by studying jet constituents
  ↪What we use: p_T, η, ϕ of each constituent



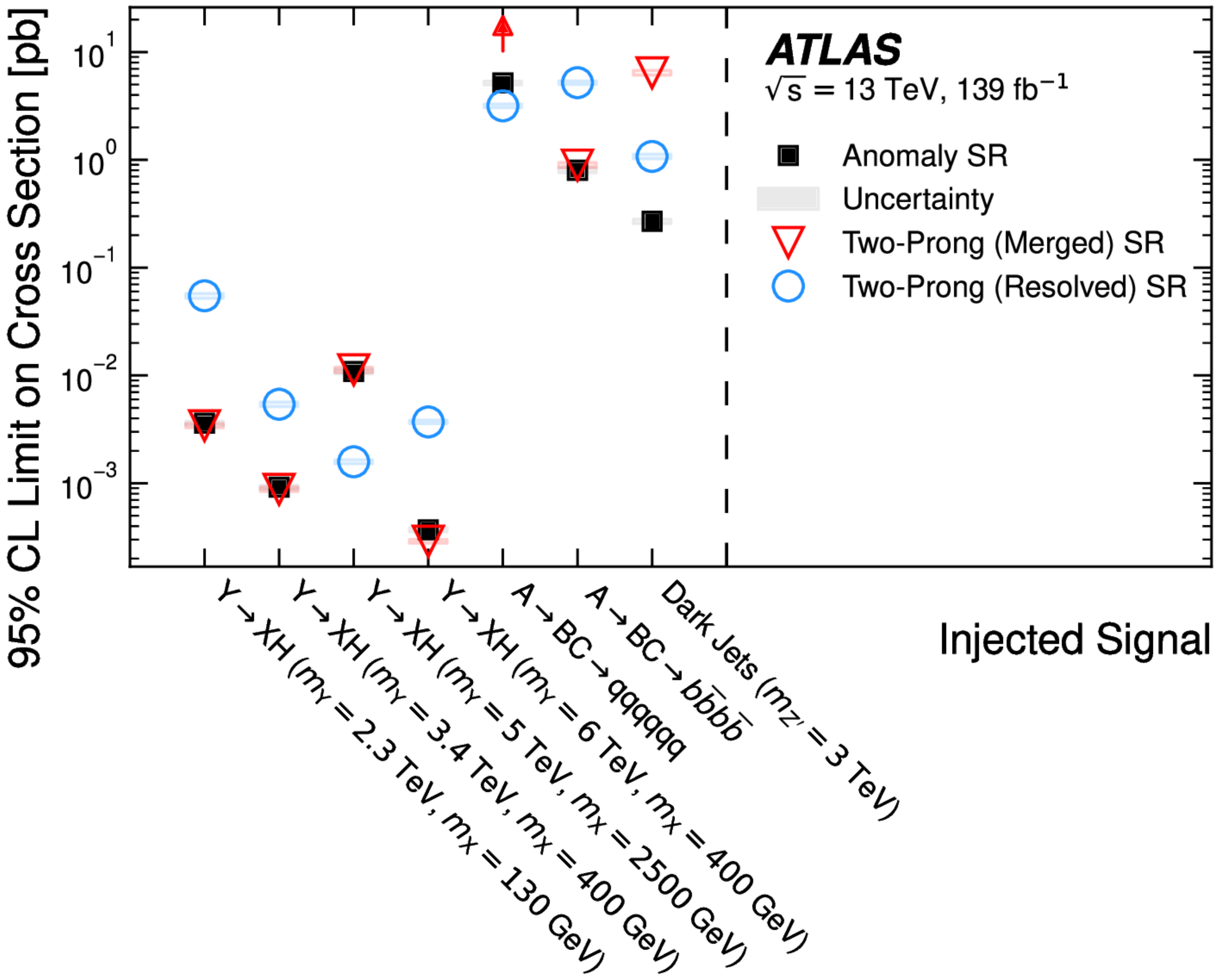
$Y \to XH$

The First Use of Unsupervised Learning on ATLAS Data

- The Y → XH analysis searches for heavy resonances decaying into a Higgs boson and new particle X in a fully hadronic final state

- Developed an unsupervised Variational Recurrent Neural Network to define an "Anomaly Signal Region)
  - ↪Recurrent neural network that updates a VAE latent space at each time step, accommodating variable-length input sequences

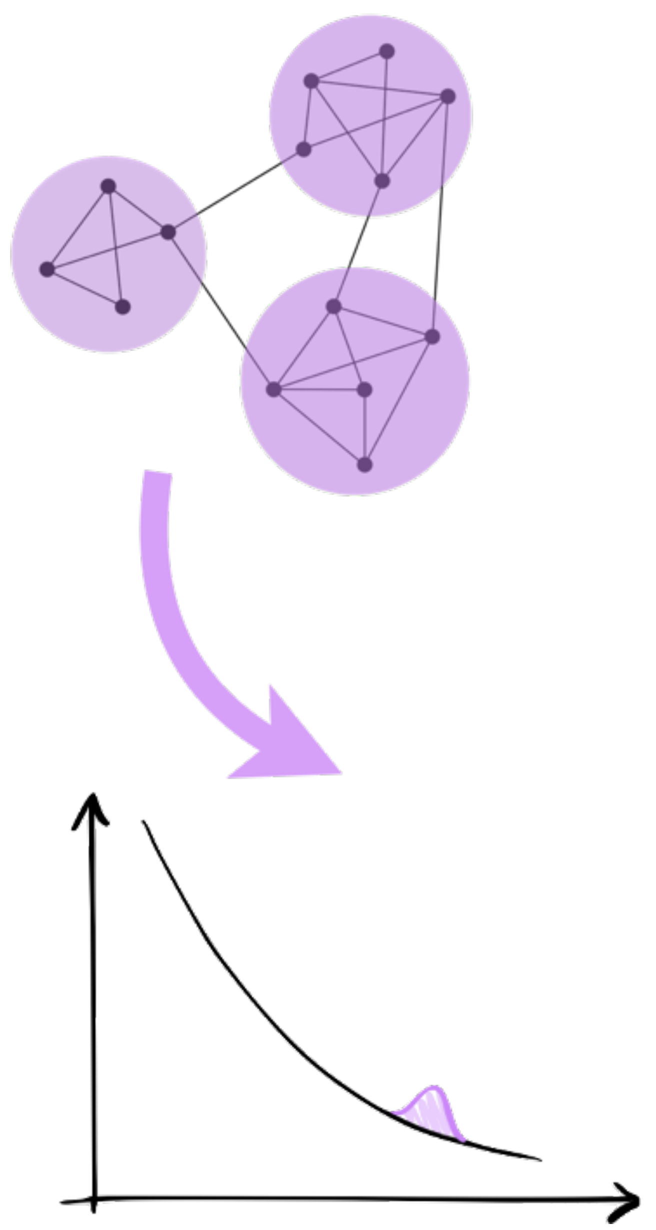
Can we improve the "classical" approach?



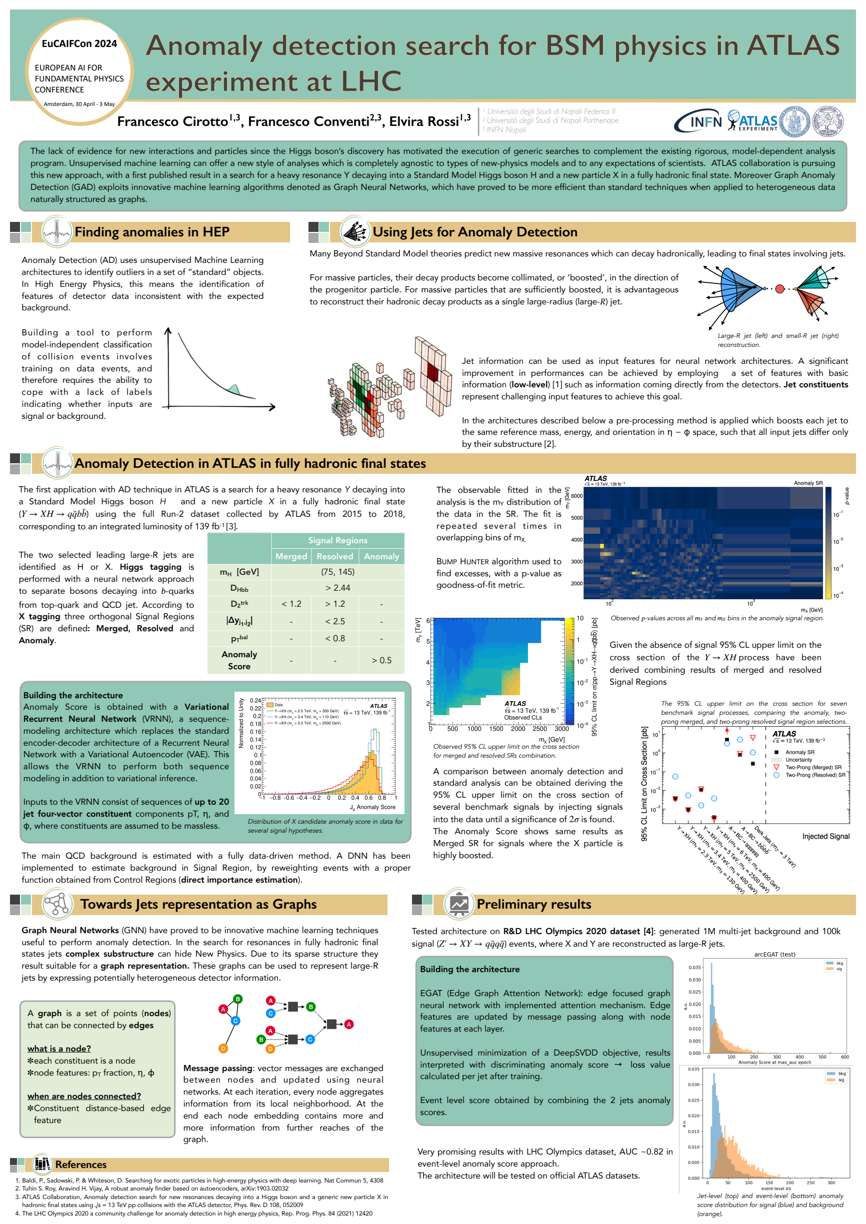
DIGGING DEEPLY WITH GRAPHS

A developing approach

- Graph-structured data are ubiquitous across science, engineering, and many other domains
  - ↪Used to describe and analyze relations and interactions
  - ↪Can encapsulate object or event information
- Our strategy: to represent jets as graphs and then apply machine learning to build an anomaly detection algorithm
  - ↪Developing both **object and event level graphs** to detect anomalies
- Preliminary results on LHC Olympics dataset



Poster 76



OmniJet-α: the first cross-task foundation model for particle physics

EuCAIFCon 2024, Amsterdam, May 1st 2024



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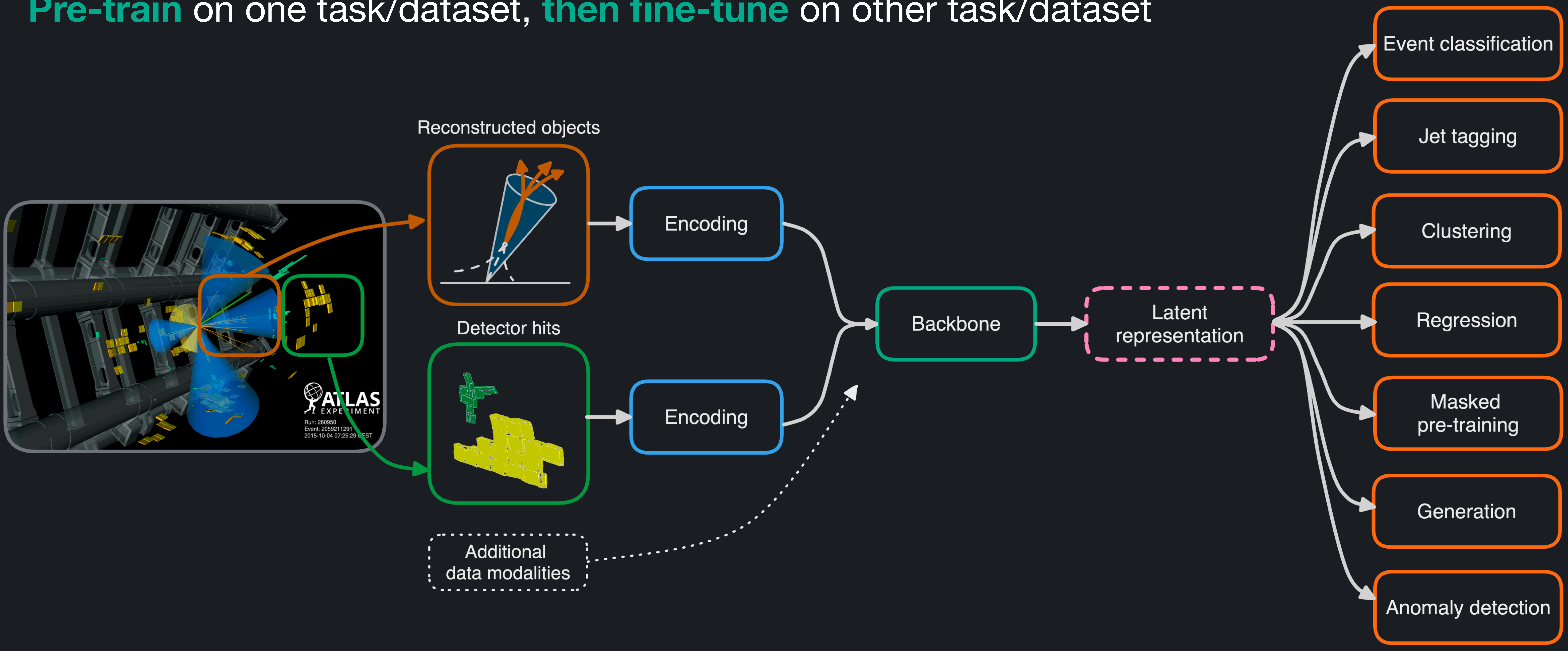
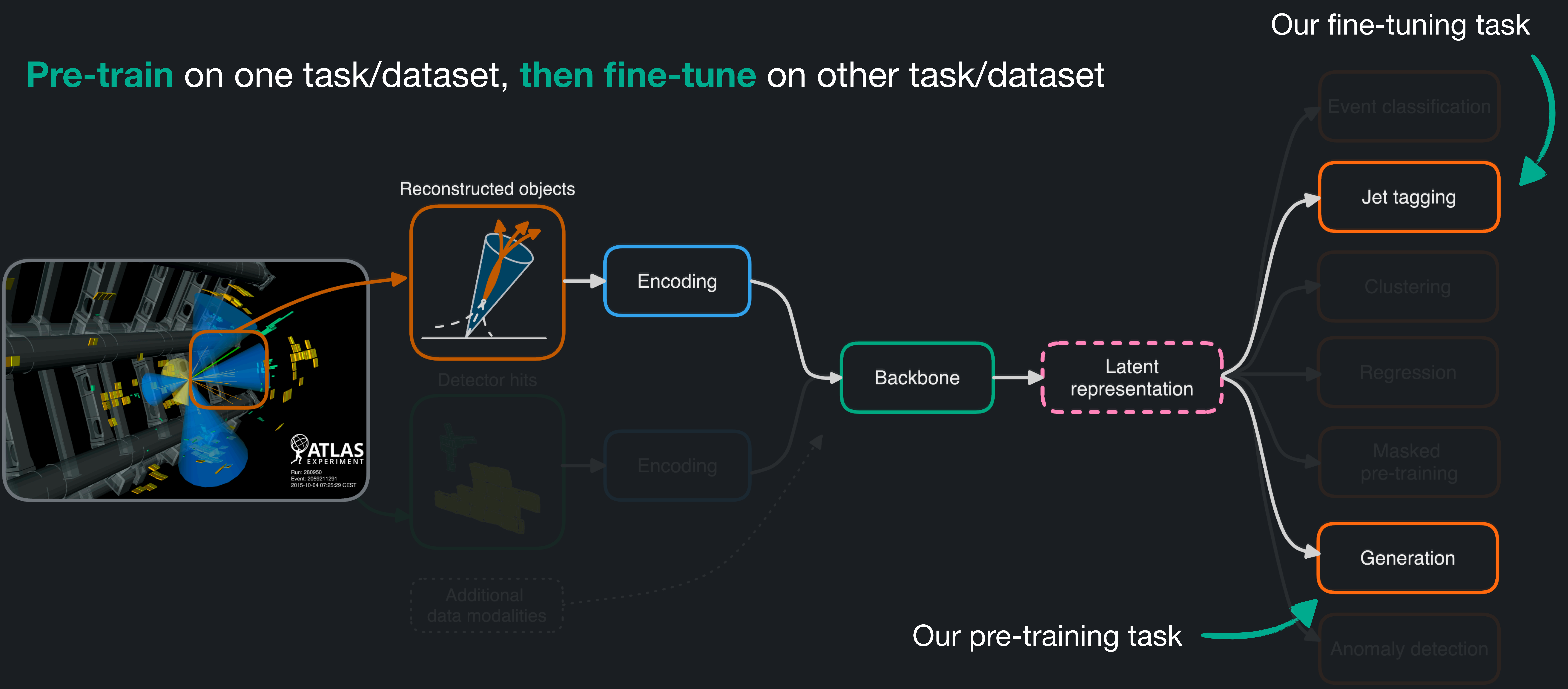
Foundation models for HEP

Pre-train on one task/dataset, **then fine-tune** on other task/dataset



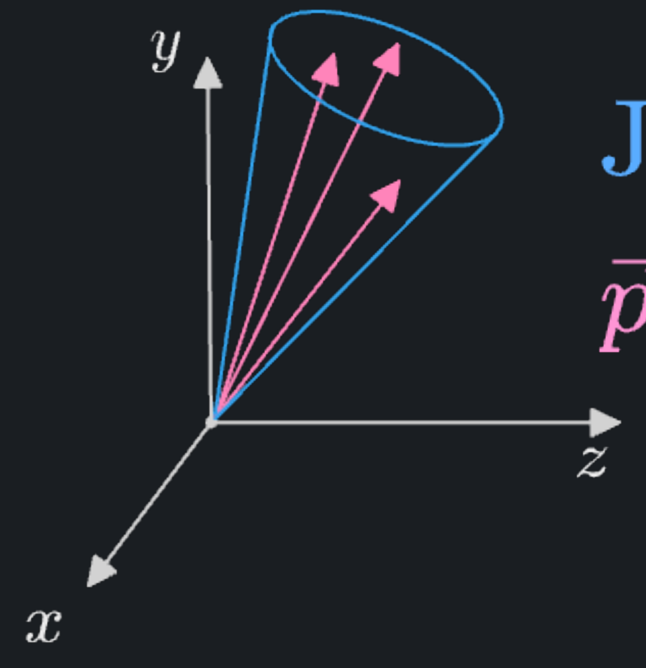
Foundation models for HEP

Pre-train on one task/dataset, **then fine-tune** on other task/dataset



Our approach

Jet constituents with **continuous features**

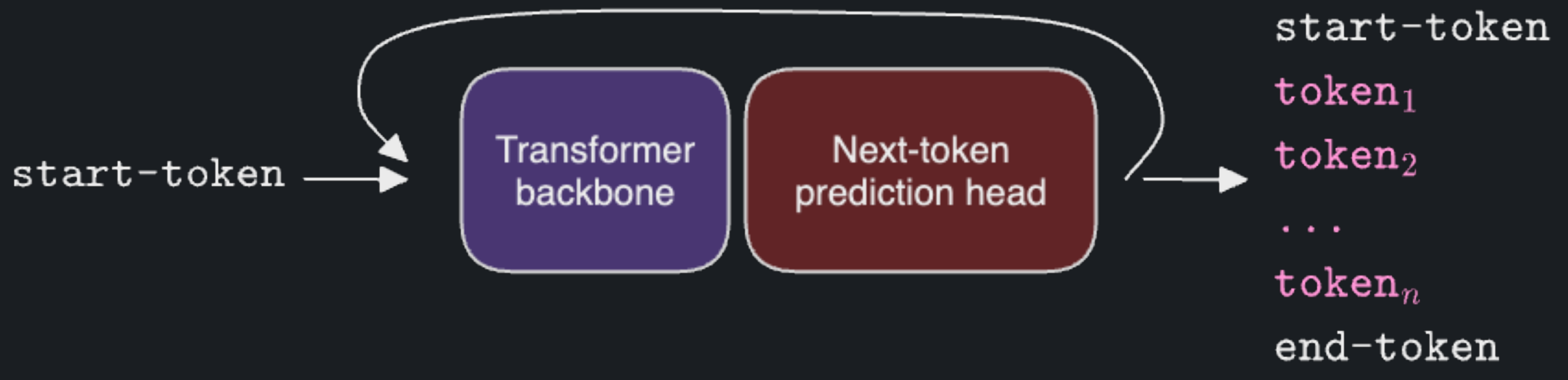


$$\text{Jet} = \{\vec{p}_1, \vec{p}_2, \ldots, \vec{p}_n\}$$
$$\vec{p}_i = (p_\mathrm{T}, \eta^{\mathrm{rel}}, \phi^{\mathrm{rel}})$$

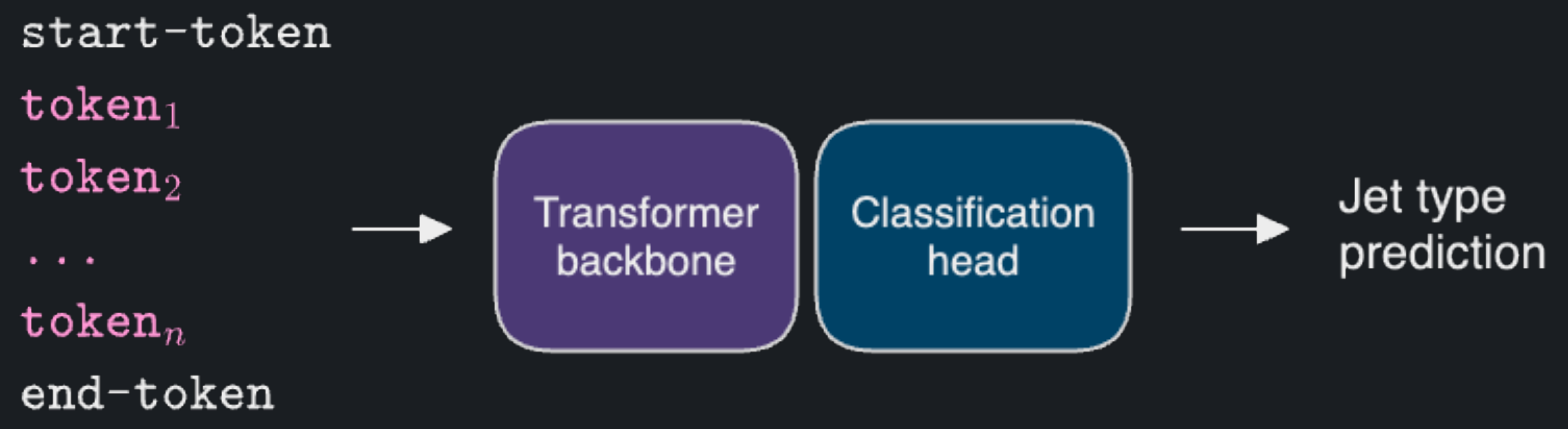
Constituents are **tokenized with a VQ-VAE**
(using the approach presented by Sam Klein earlier)

$$\text{Jet} = \{\texttt{start-token}, \texttt{token}_1, \ldots, \texttt{token}_n, \texttt{end-token}\}$$
$$\texttt{token}_i = \text{integer value} \in [1, \ldots, 8192]$$

Unsupervised pre-training of transformer backbone on generative task (next-token prediction)

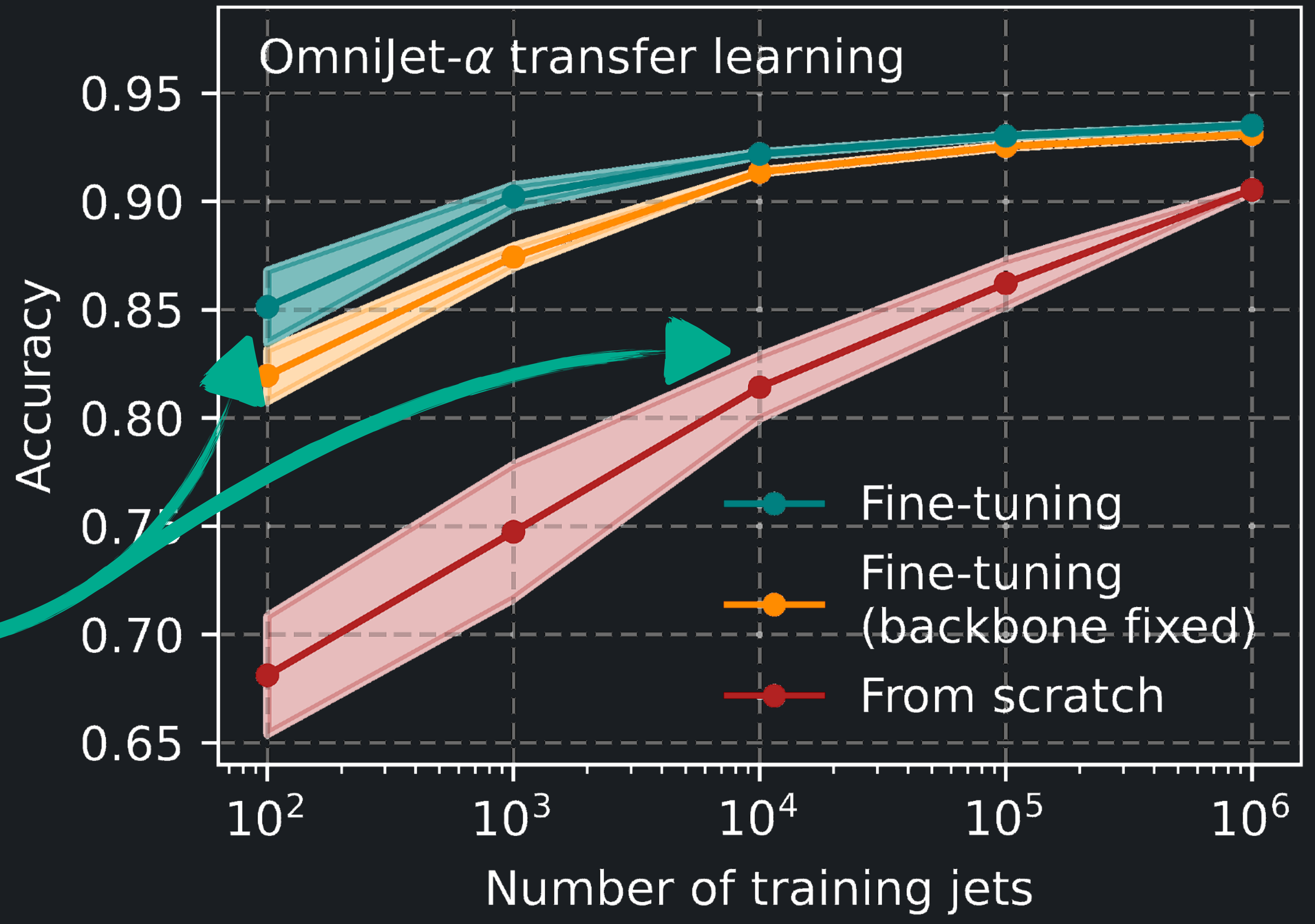


Fine-tuning to classification task:
Swap model head and copy over the weights from the pre-trained backbone



Does generative pre-training help for classification?

- Classification: $t \to bqq'$ vs. q/g jets
- Generative pre-training with both jet types
- **Pre-trained / fine-tuned model** (● ●) reaches same performance as from scratch training with **100-1000x less training samples**



→ ***Generative pre-training is a promising target for unsupervised pre-training in HEP***

Poster number: **54**

Applying hierarchical autoregressive neural networks for three-dimensional Ising model

Poster no. 74

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3D Ising model

Autoregressive neural network:

$$q_\theta(\mathrm{s}) = \prod_{i=1}^{N} q_\theta(s_i | s_1, s_2 \ldots . s_{i-1})$$

Hierarchical structure:

$$p(\mathrm{s}) = p(\mathrm{B}(\mathrm{s}))p(\mathrm{I}(\mathrm{s})|\mathrm{B}(\mathrm{s}))$$

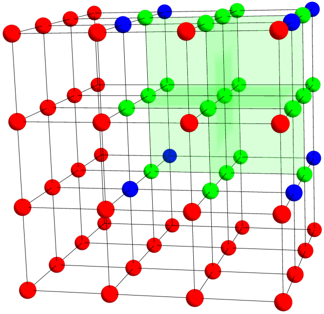

Figure: Scheme of hierarchical decomposition of $4 \times 4 \times 4$ cube

Neural Importance Sampling:

$$Z = \frac{1}{N}\sum_{i=1}^{N} \frac{e^{-\beta E(s_i)}}{q_\theta(s_i)}$$

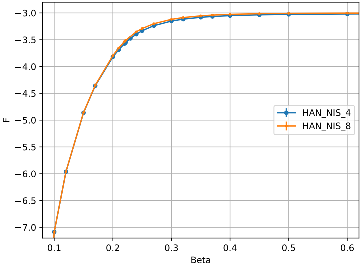

Figure: Free energy of β for HAN neural network

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