

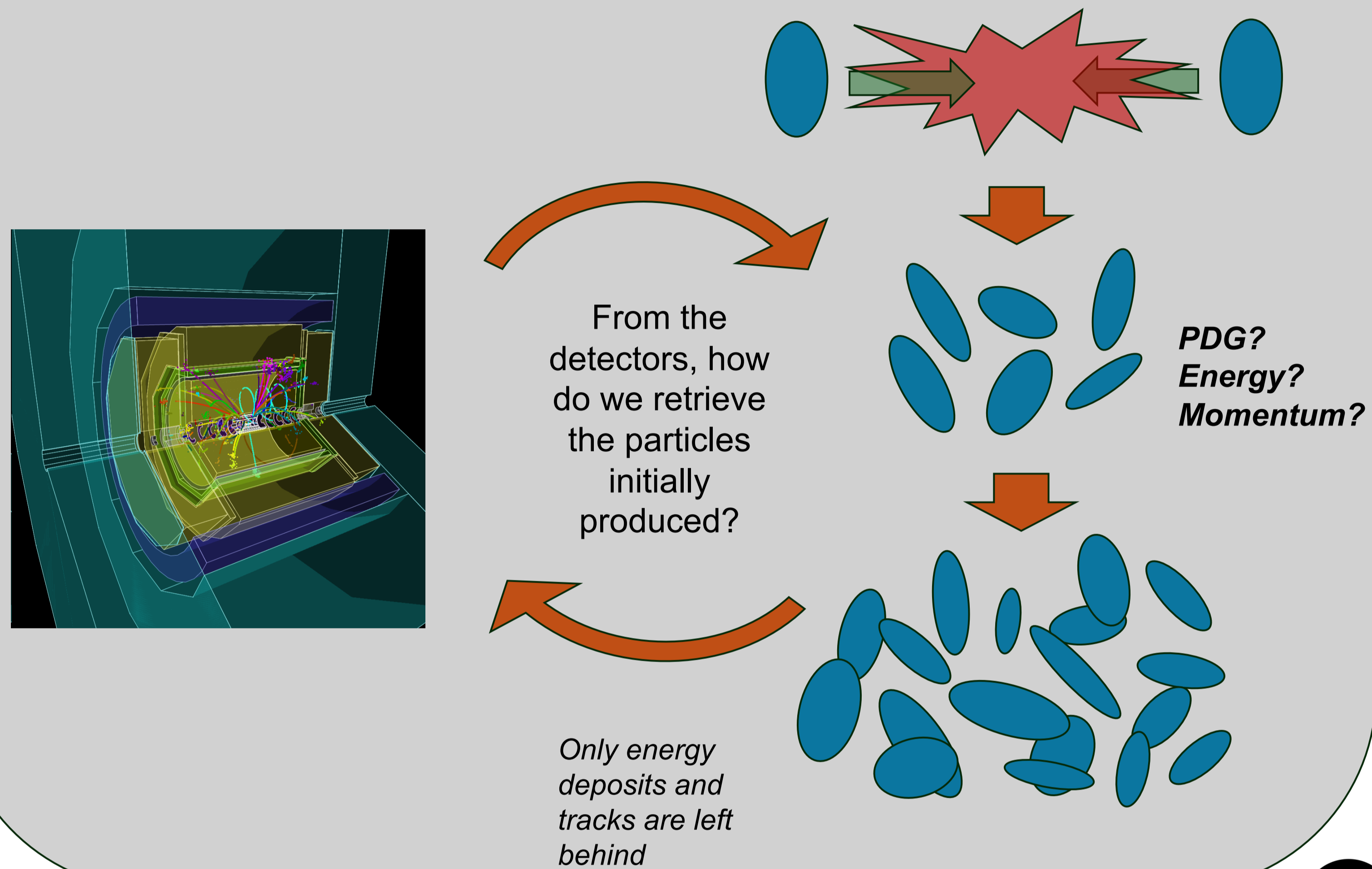
We reconstructed photons from energy deposits by transforming particle reconstruction.

Particle-flow reconstruction with Transformer

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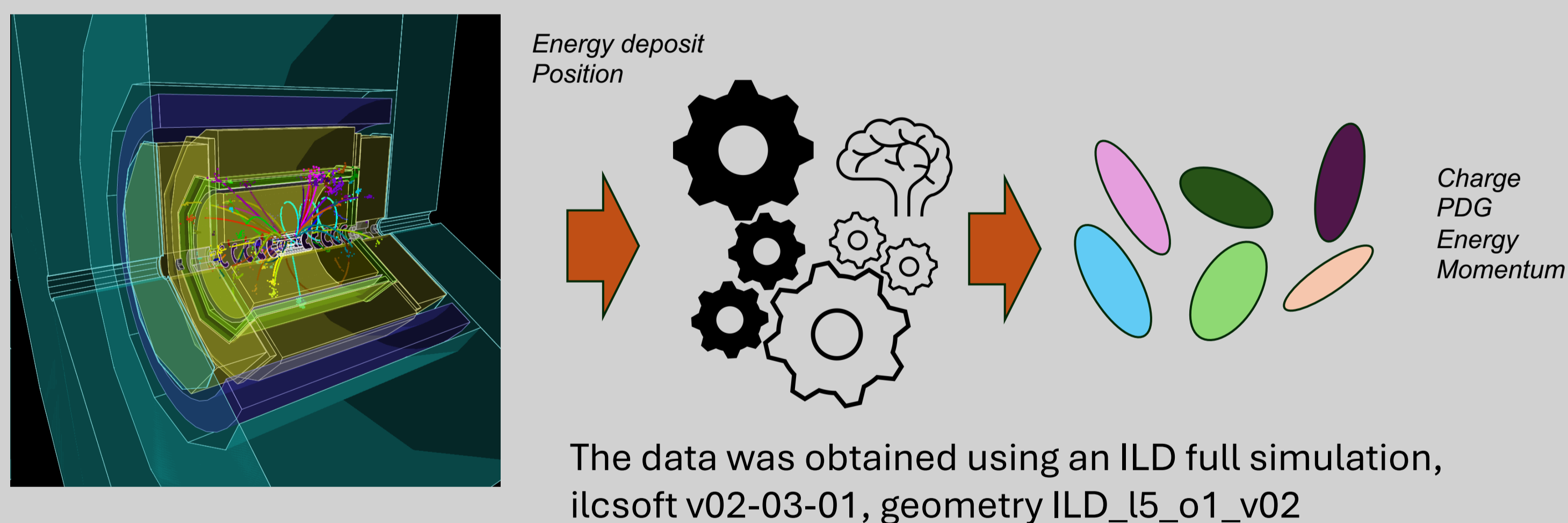
Background:

Due to the interaction between particles and matter, the initial energy of an incoming particle into a detector is scattered in hits located at different positions, forming a cluster. This renders the cluster of reconstructing the initial particle notoriously difficult and several algorithm, called Particle Flow Algorithms (PFAs), have been developed to tackle this.



Methodology:

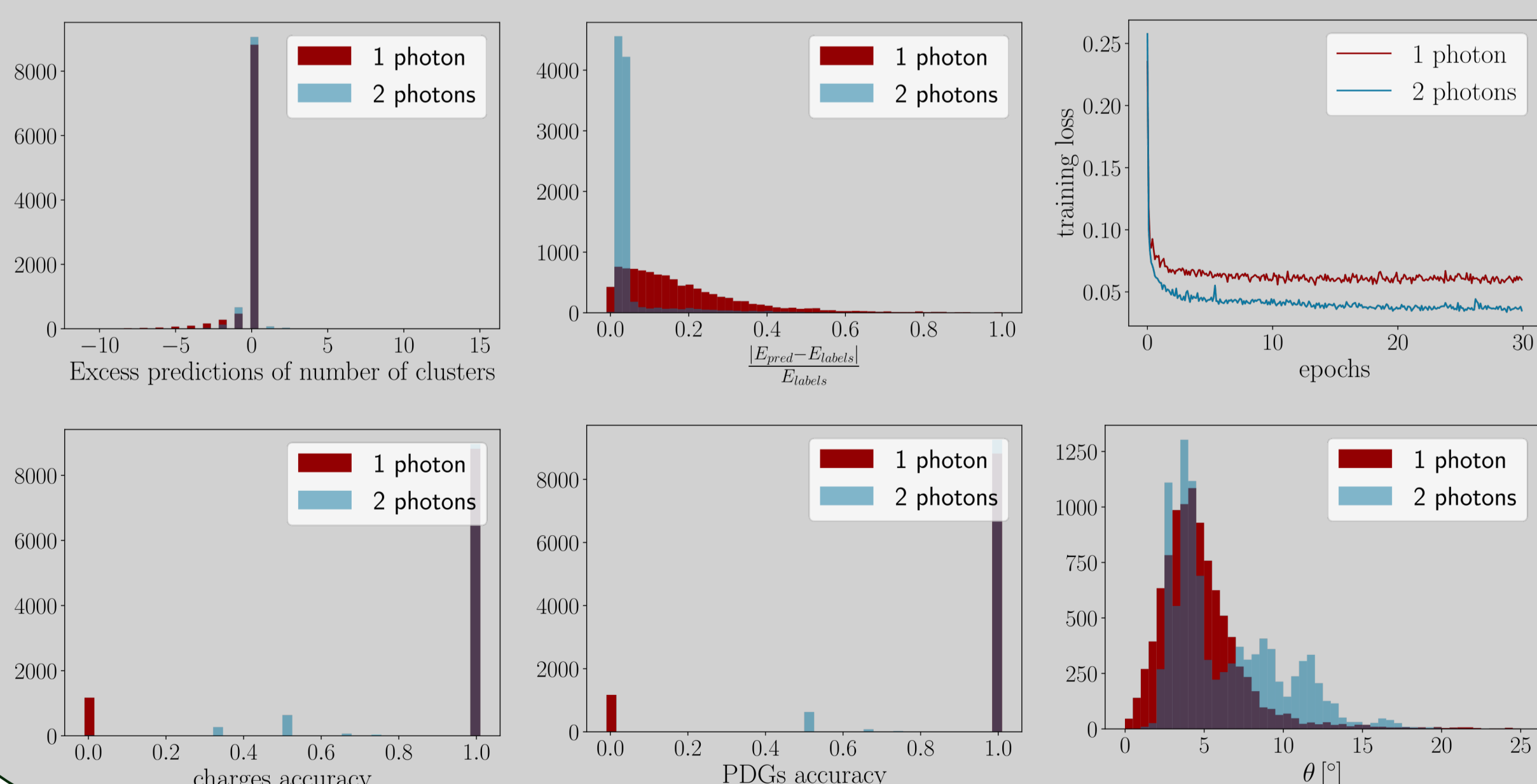
Using a network architecture first developed in language models, a Transformer, we are reconstructing particles using only the energy deposits and their positions in the calorimeters.



Results

- Models are tested against clusters generated by either a **single** or **two photons**
- Maximum accuracy is not achieved since photons can split into particles/antiparticles, etc...

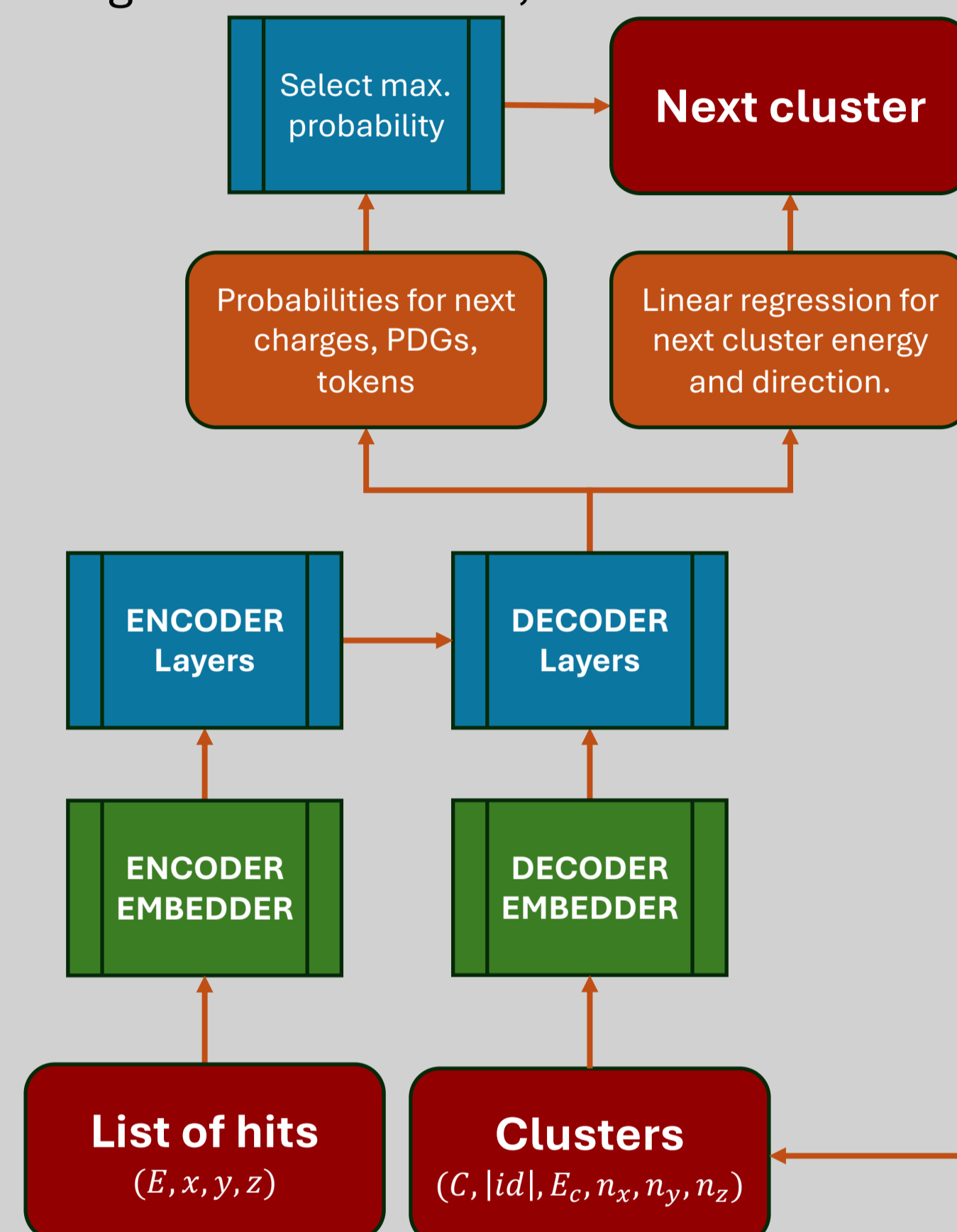
Accuracies are calculated by a one-to-one comparison between overlapping predictions and labels



- Single photons:** logarithmic distribution of 10 to 100 GeV particles in random directions. 100k events.
- 2 photons:** Fixed energy at 10 GeV, θ fixed at 85 degrees. ϕ random. The 2 photons are separated by an opening angle of 100 mrad.

Network Architecture:

The architecture is heavily inspired by the original Transformer detailed in *Attention is All you Need* by Vaswani et al. (2017). **Mean Square Error** is used for continuous degrees of freedoms, whereas **Cross Entropy** is used for discrete quantities.



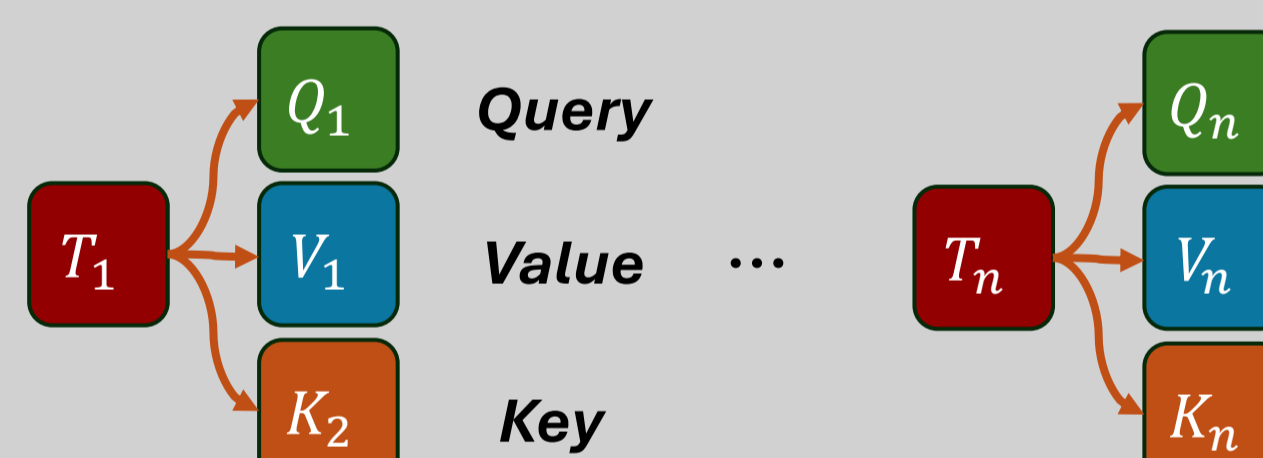
Hits are characterised by their positions in the calorimeters and energy deposits.

Clusters contain information of particles before passing through the detectors. These are:

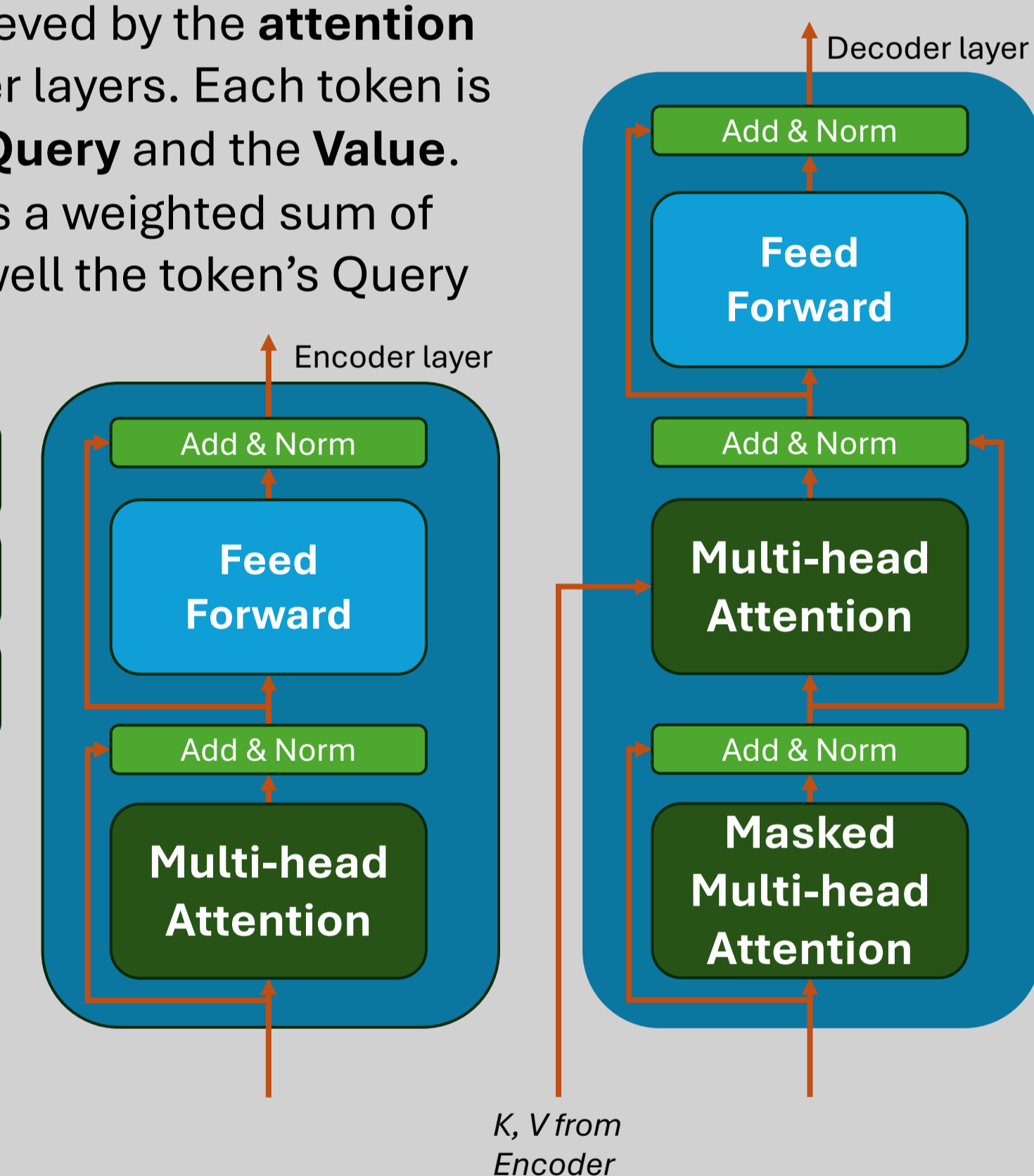
- Its charge, C
- The absolute value of its PDG number, $|id|$
- Its energy, E_c
- Its direction, (n_x, n_y, n_z)

At each **iteration**, the model predicts the **next cluster** by using information contained in the hits and clusters from **previous iterations**. The process is stopped when an end of sequence token is predicted.

Information in hits and clusters is retrieved by the **attention** mechanism in the encoder and decoder layers. Each token is projected onto 3 vectors: the **Key**, the **Query** and the **Value**. During attention, tokens are updated as a weighted sum of the Values, with weights given by how well the token's Query are aligned with the Keys.



$$T'_i = \text{Attention}(Q_i, K_j, V_j) = \sum_{j=1}^n \text{softmax}\left(\frac{Q_i K_j^T}{\sqrt{d_k}}\right) V_j$$



4

Conclusion

- Current architecture shows reasonable results with simplified datasets of clusters formed by one or two particles

Perspective of future work

- Increasing the **complexity** of the dataset using multiple **taus** or **jets** to form the clusters
- Focusing on predicting the correct numbers of clusters first, trying different architectures and hyperparameters.

5

More information and code can be found on the GitHub repository



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