



Implementing a Transformer as a Particle Flow Algorithm

06.06.2024

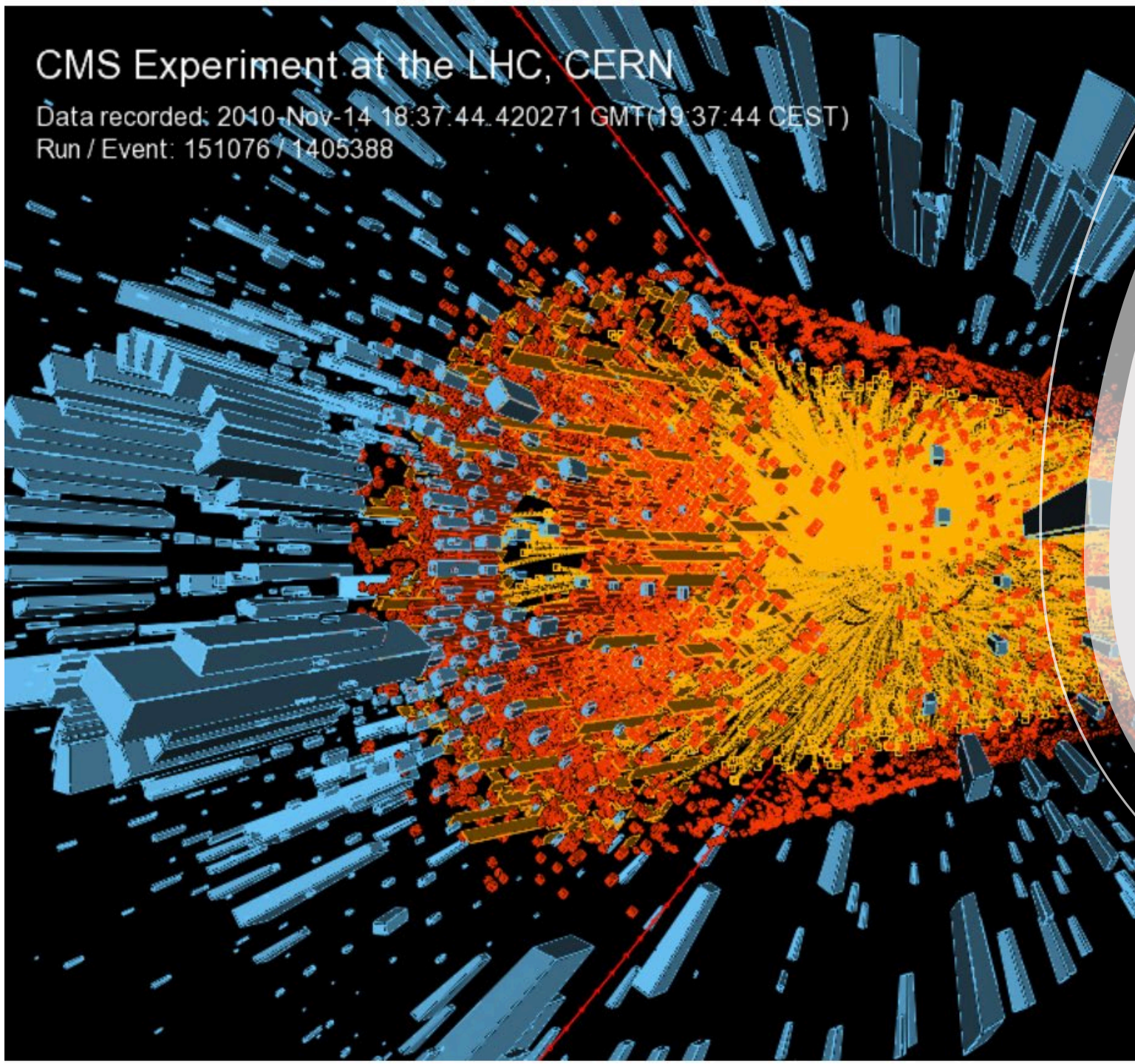
ILANCE Intern Fest

Paul Wahlen,

Supervised by Taikan Suehara & Junping Tian

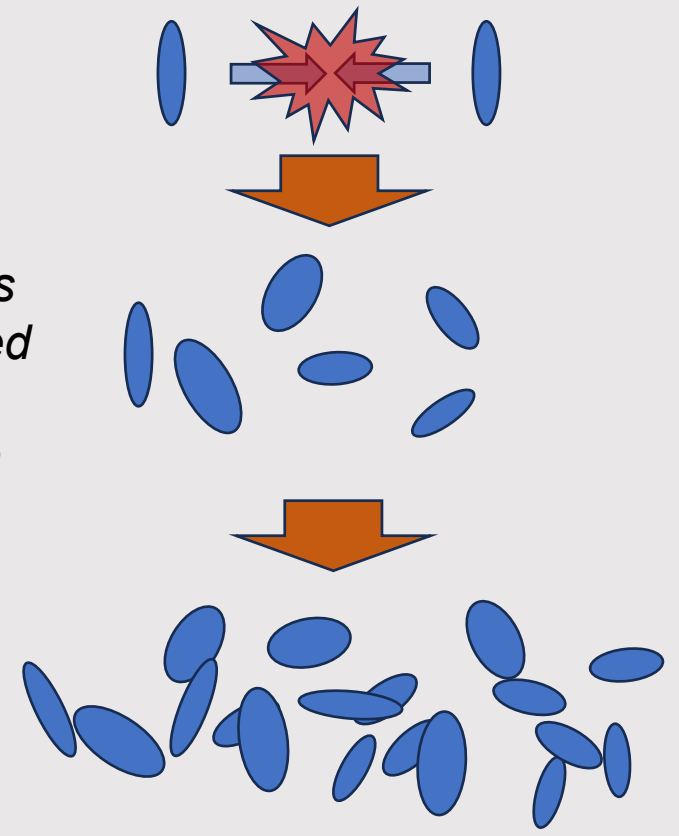
CMS Experiment at the LHC, CERN

Data recorded: 2010-Nov-14 18:37:44.420271 GMT(19:37:44 CEST)
Run / Event: 151076 / 1405388



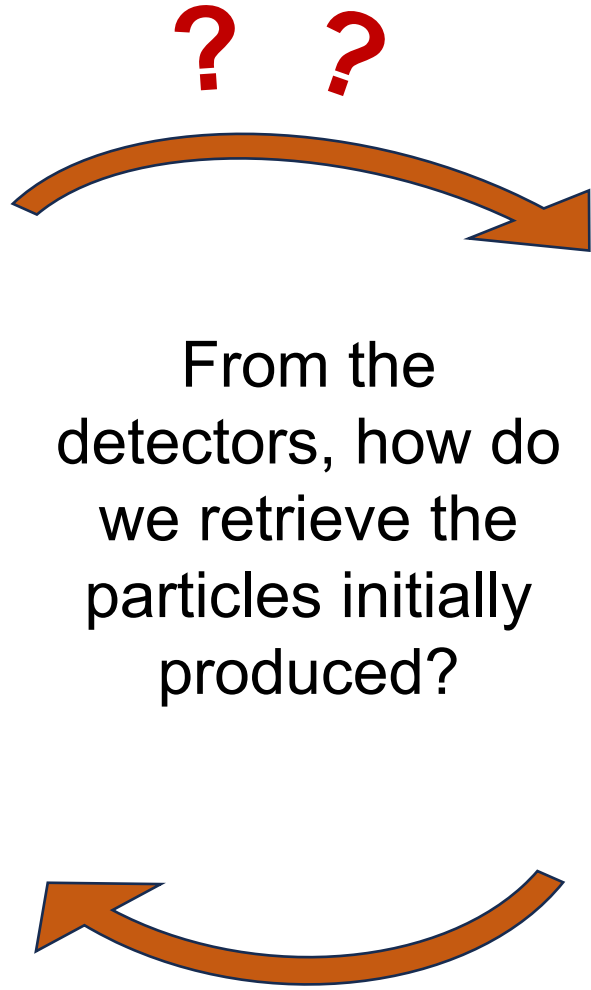
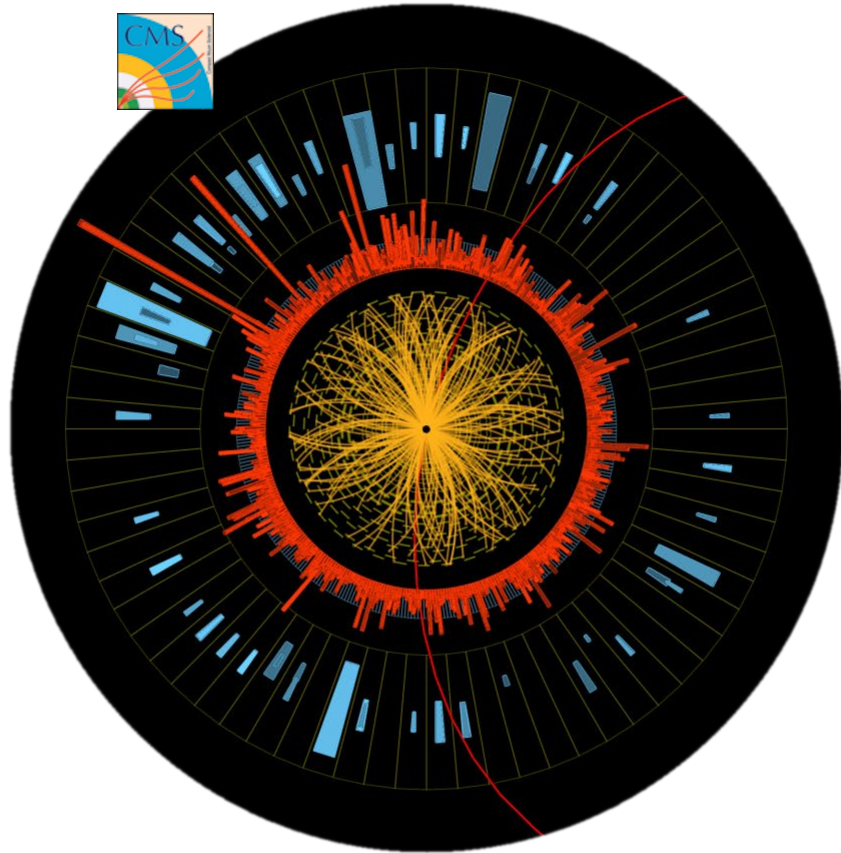
The problem with particle accelerators...

Particles produced during collision

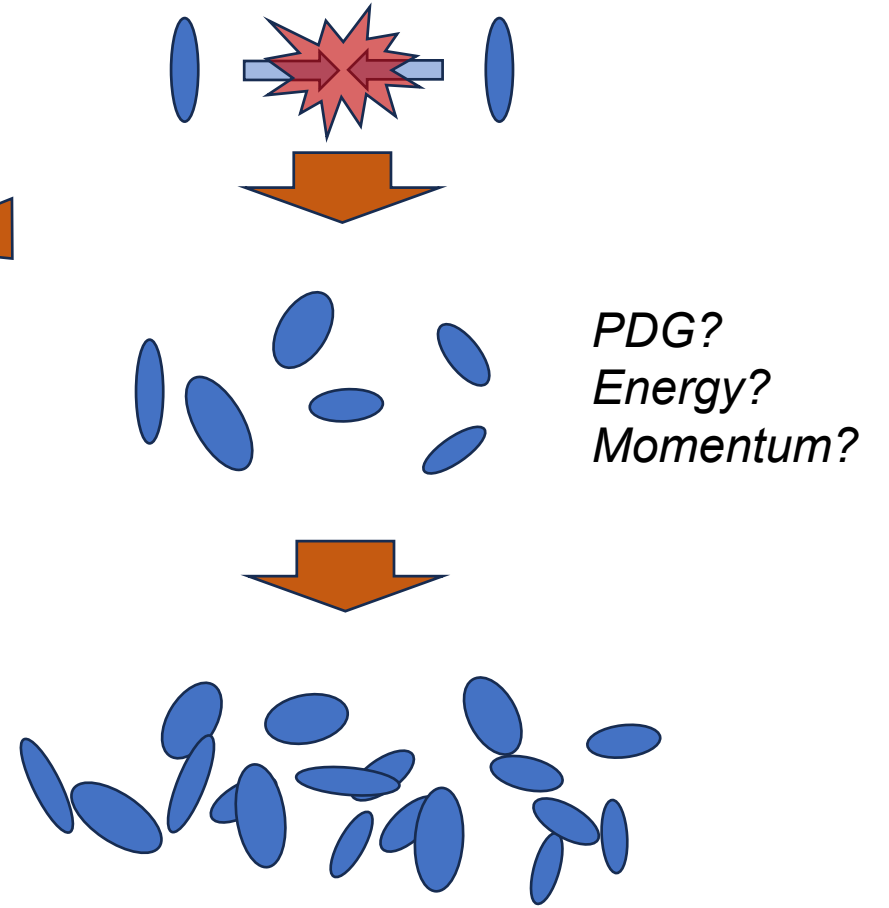


Going through the detectors...

The problem with particle accelerators...

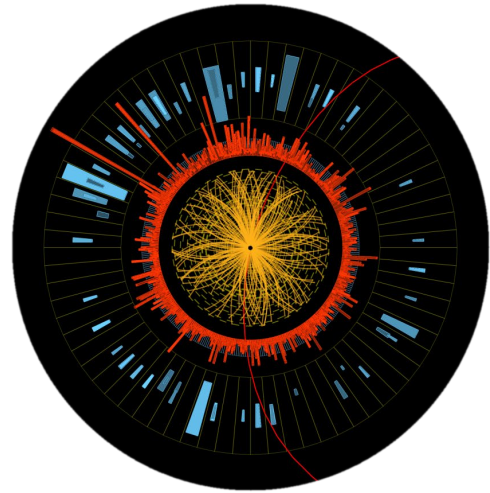


From the detectors, how do we retrieve the particles initially produced?

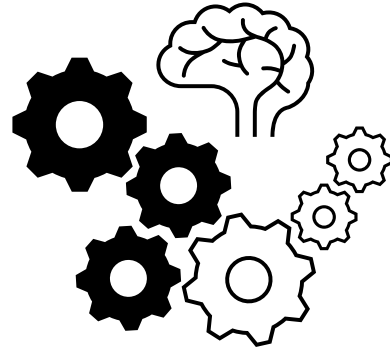
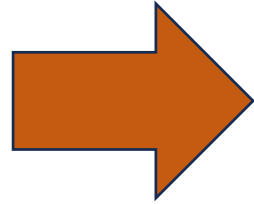


Only energy deposits and tracks are left behind

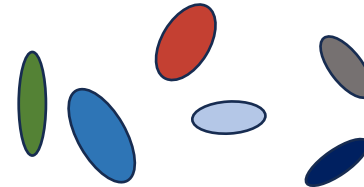
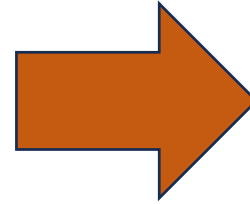
A possible solution (hopefully)



*Energy deposit
Position*

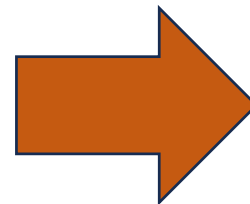
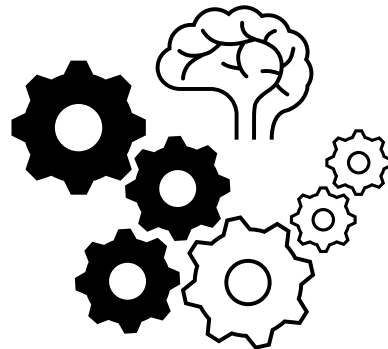
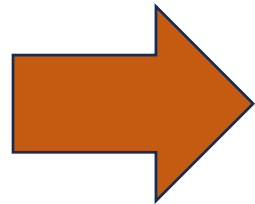


*Charge
PDG
Energy
Momentum*



Looks somewhat similar to a well known problem: machine translation

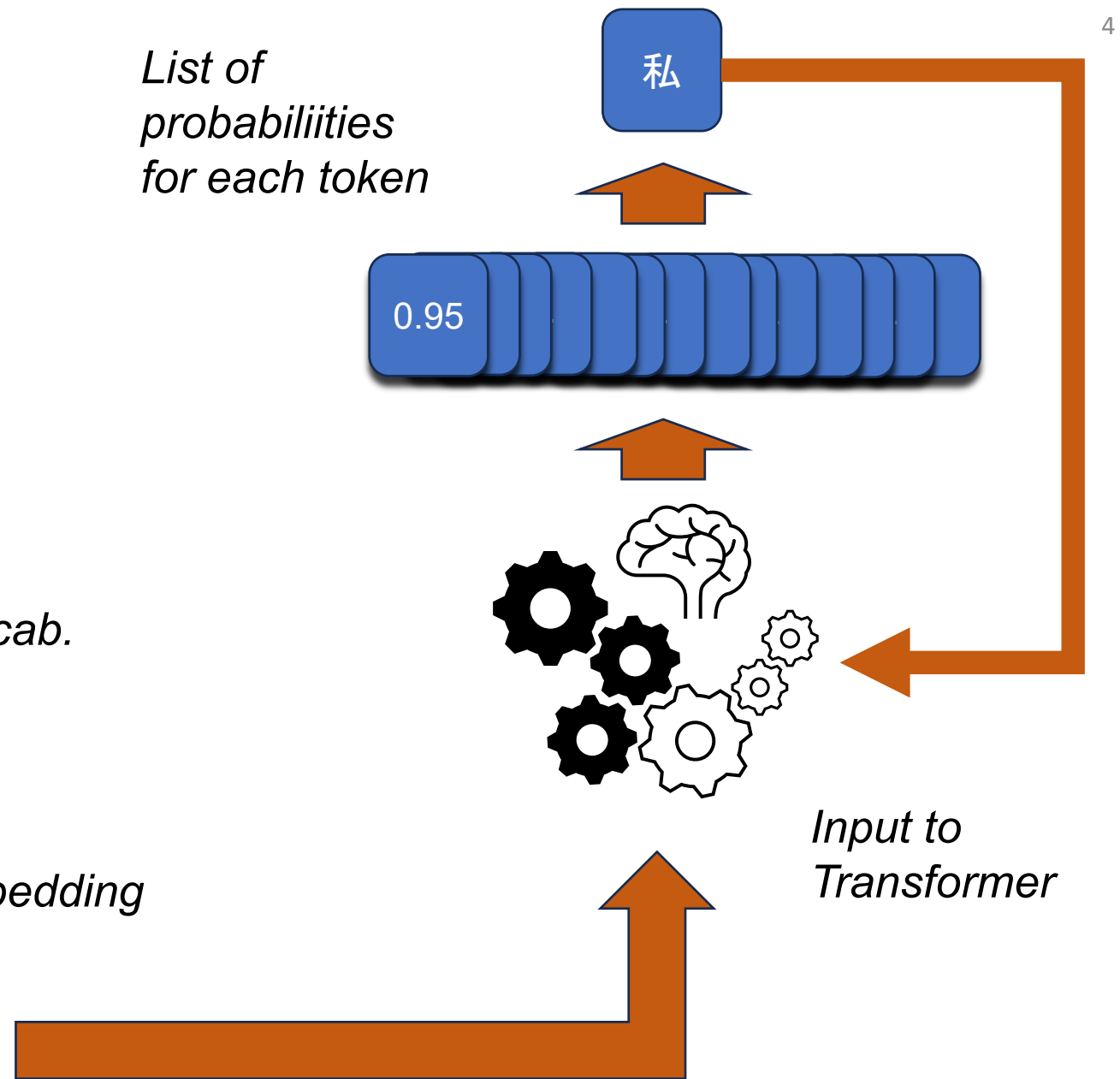
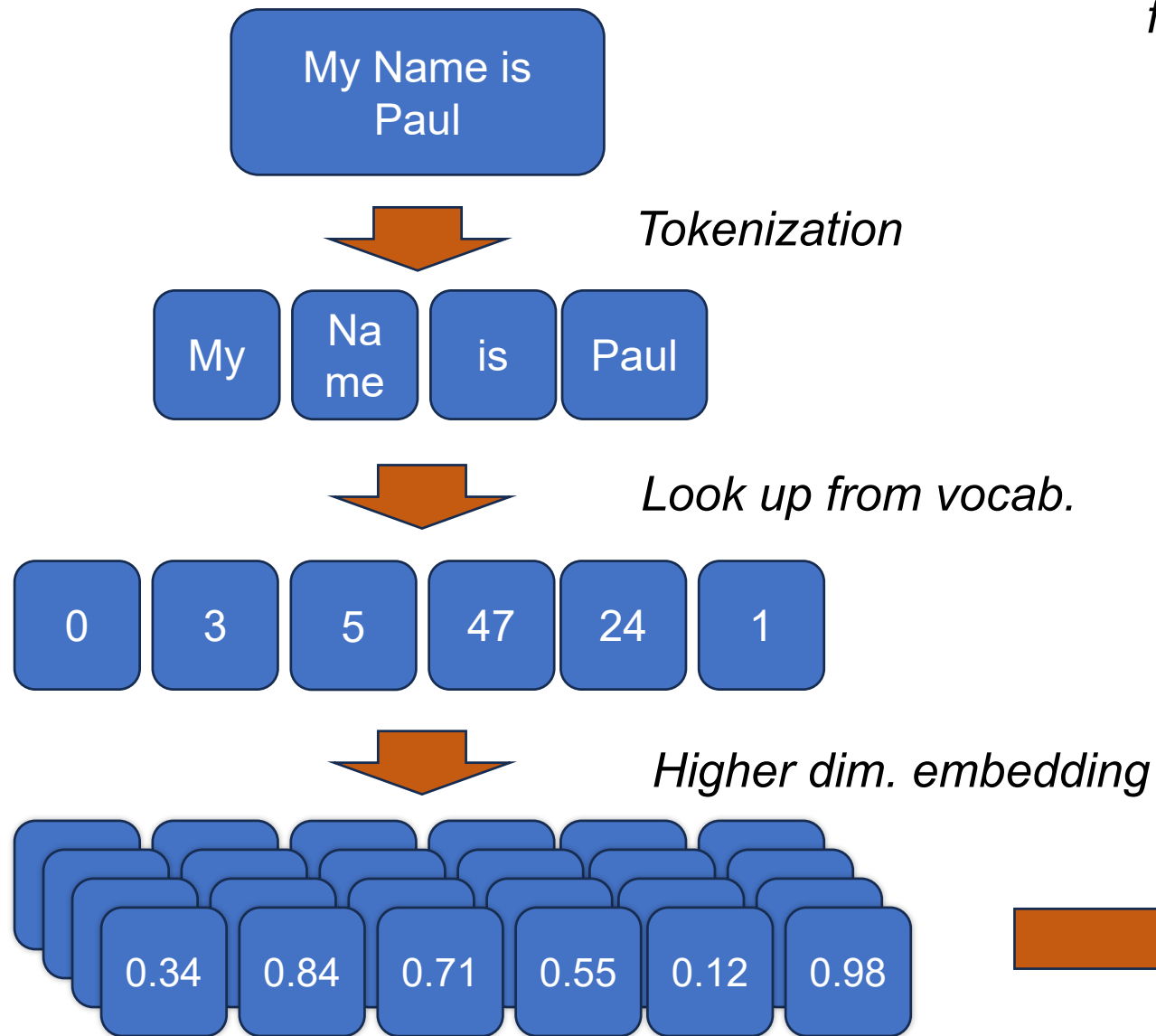
My name is Paul



私はポールです

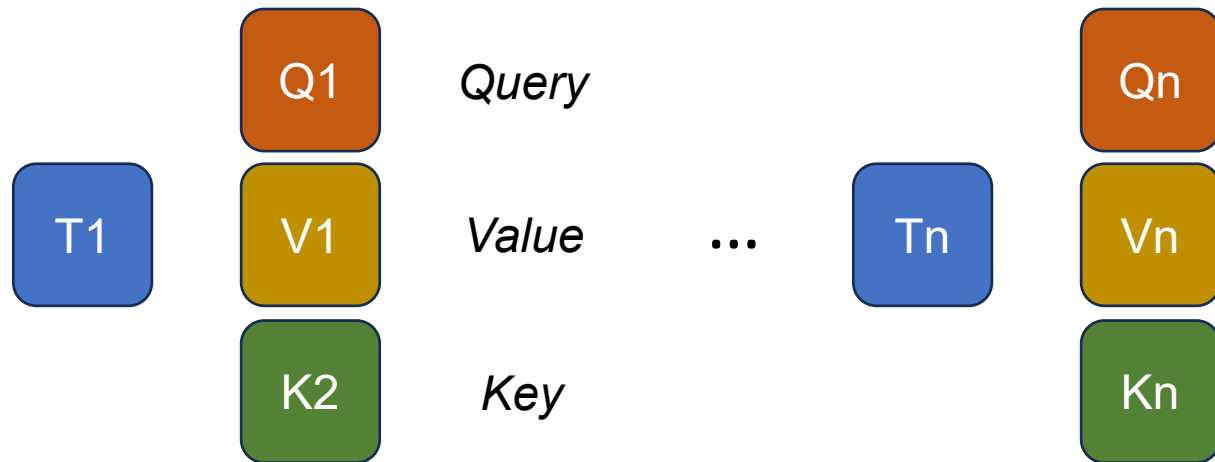
Nowadays, achieved using a Neural Network called Transformer

Machine Translation

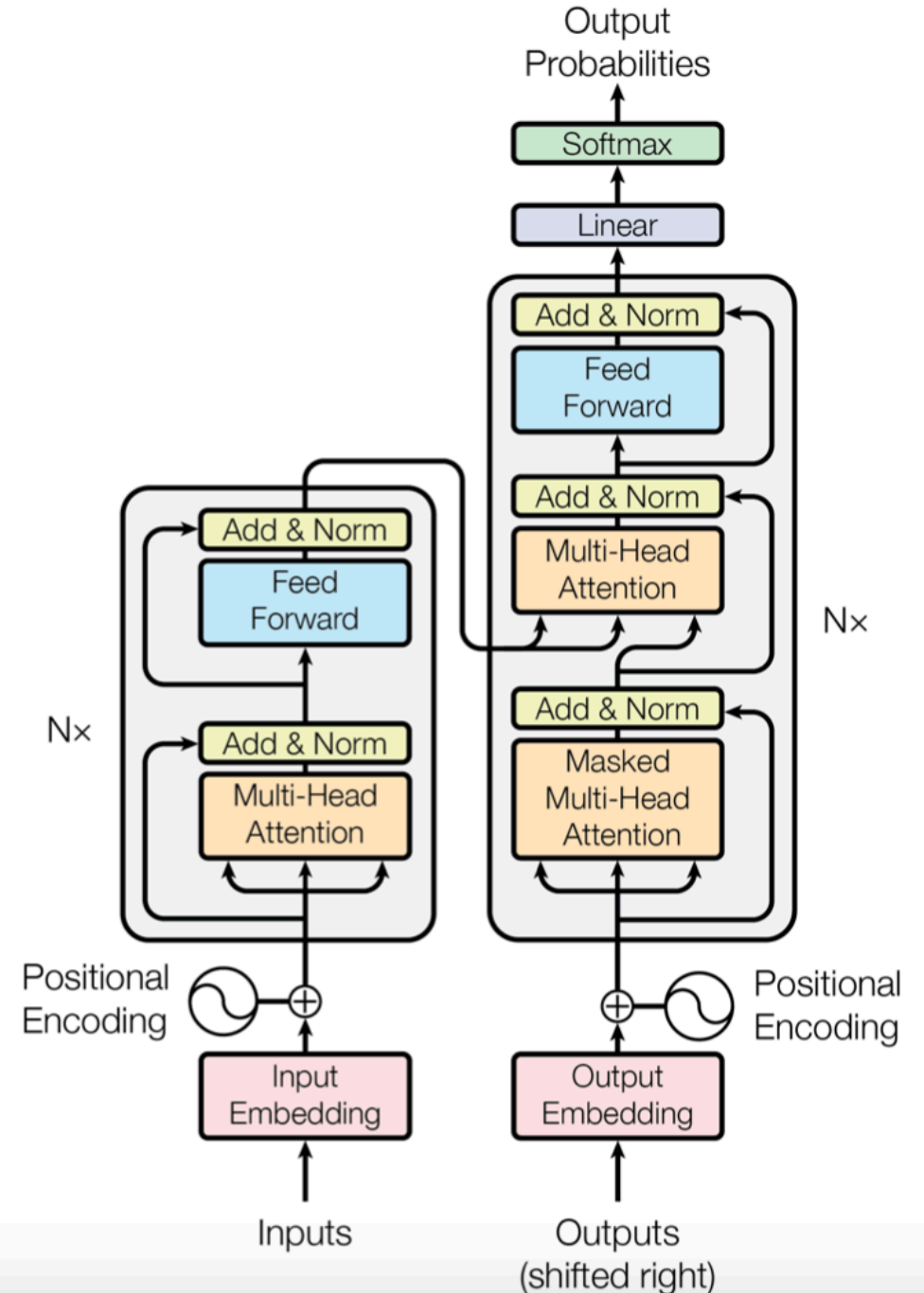


Inside a transformer

Multi-head Attention: Allows tokens to communicate with each other to better understand the context in which they are used.



$$\text{Attention}(Q, K, V) = \text{softmax} \left(\frac{QK^T}{\sqrt{d_k}} \right) V$$



Shaping the output we want

- Determined during training, when the model adjusts its parameters to minimize *the loss function*
- Good prediction means that the "distance" between model output and truth is small.

Categorization



Cross-Entropy

Regression



Mean Squared Error

In both cases, the further away from the truth, the larger the value of the loss function

Project concept

Using a Transformer to predict the particles generating the clusters

	Sequence to Sequence	Physics
Input	Sentence	List of hits from 1 event
Output	Machine translation of Seq	List of clusters to which belongs each hit
token	Depends, words/ few char.	1 hit
Special tokens	bos, eos, unkwn, pad	bos, eos, sample, pad

$$\begin{pmatrix} \text{bos} & \text{hit} & \text{hit} & \text{eos} & \text{pad} & \text{pad} \\ \text{bos} & \text{hit} & \text{hit} & \text{hit} & \text{eos} & \text{pad} \\ \text{bos} & \text{hit} & \text{eos} & \text{pad} & \text{pad} & \text{pad} \end{pmatrix}$$

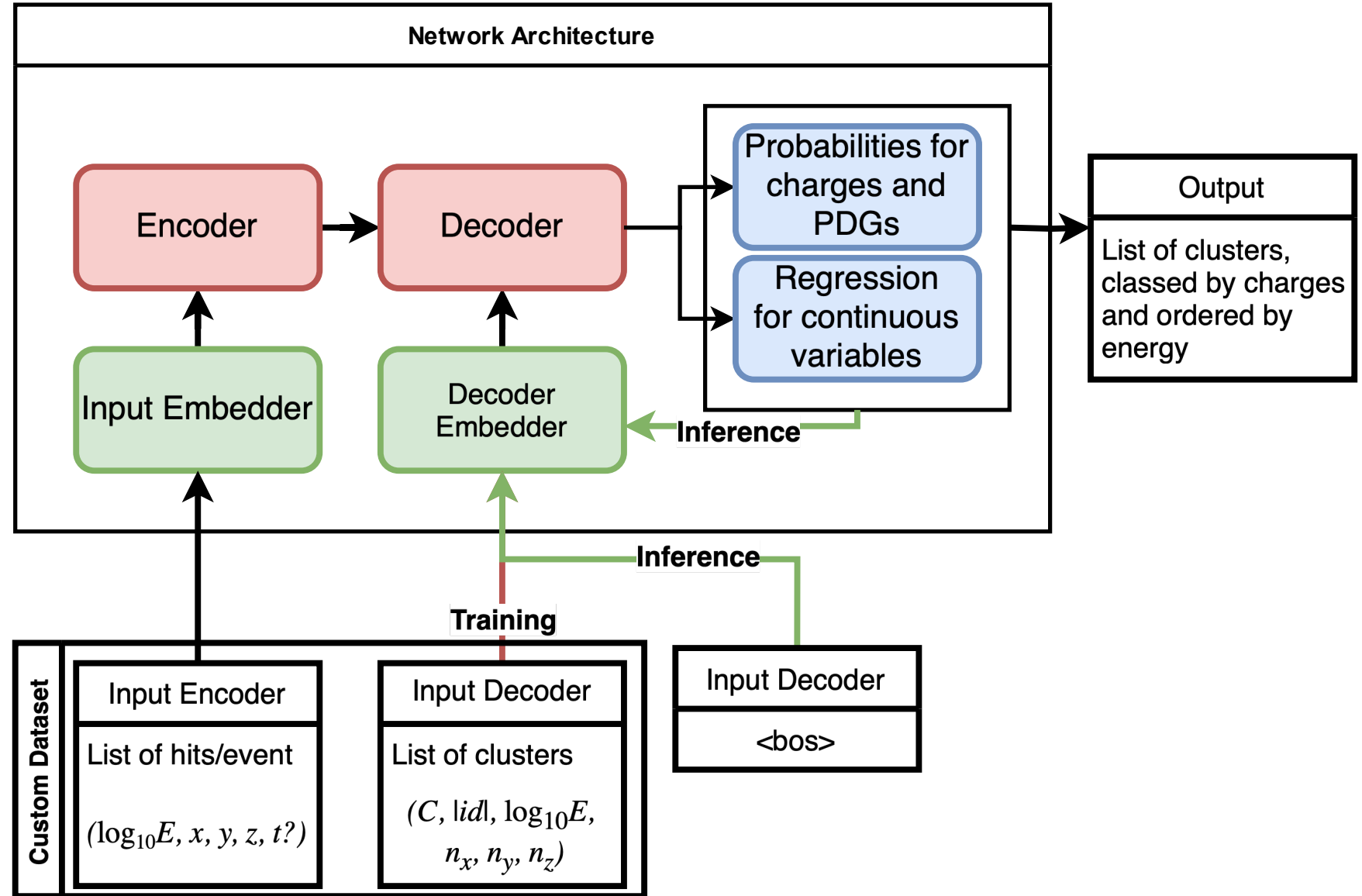
- Special symbols and general formatting of the raw dataset is done by a custom Pytorch's Dataset

General Architecture

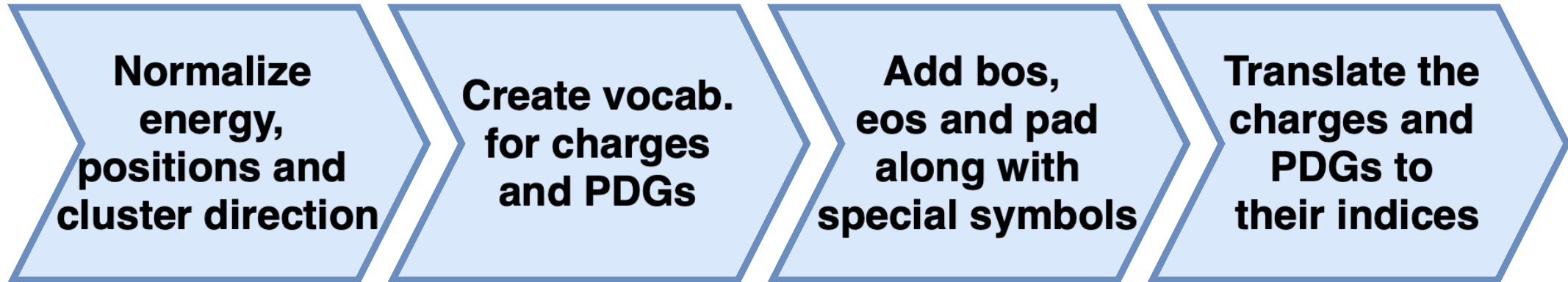
Cluster information are obtained from MC Particle truth information.

3 loss functions, weighted by hyperparameters:

- Most common particle ids form vocabulary:
 $\gamma, K_S, K_L, K^+, \mu^-, p, n, \pi^\pm, e^-$
CrossEntropyLoss
- Charges form other vocabulary. -1, 0, 1. Also CrossEntropyLoss
- Continuous variables are obtained by regression.
MSE for the loss function.



Data Processing



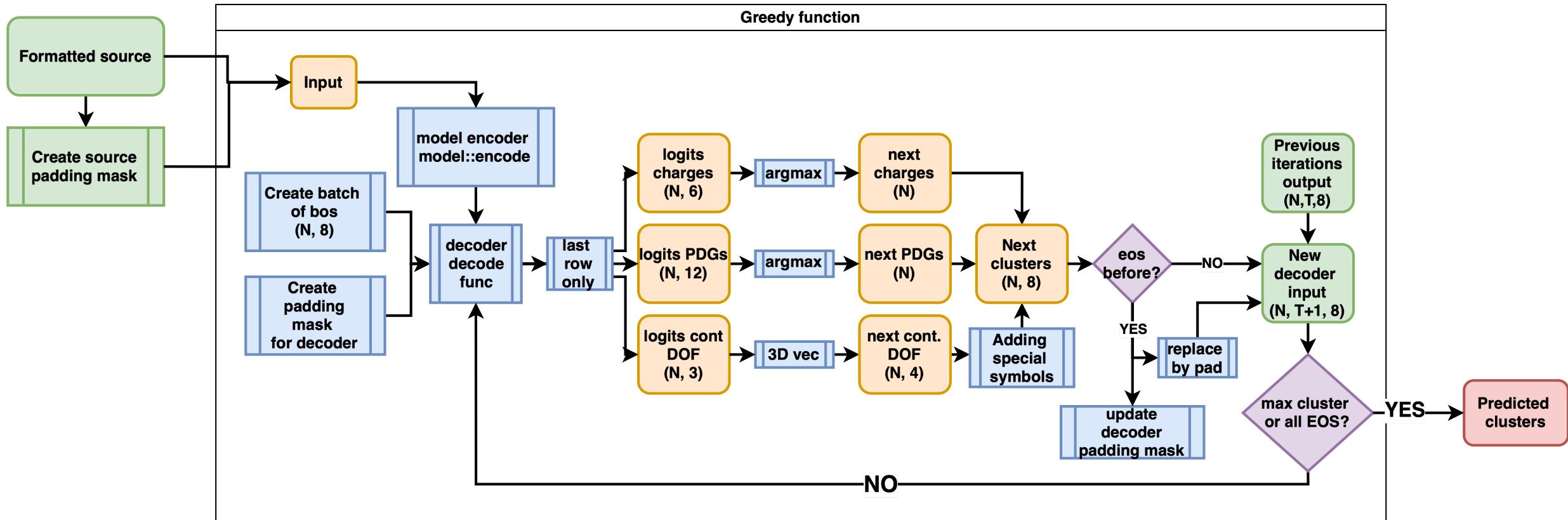
pad: $(-150, -150, 0, 0, 0, 0, 0, 1) \mapsto (0, 0, 0, 0, 0, 0, 0, 1)$

bos: $(-100, -100, 0, 0, 0, 0, 0, 1) \mapsto (1, 1, 0, 0, 0, 0, 1, 1)$

eos: $(-50, -50, 0, 0, 0, 0, 0, 1) \mapsto (2, 2, 0, 0, 0, 0, 1, 0)$

sample: $(-1, 11, E, n_x, n_y, n_z, 0, 0) \mapsto (3, 5, E, n_x, n_y, n_z, 0, 0)$

Inference



Conclusion

- First implementation now finished and in training
- Need to play around with the different parameters to get best performances

