# [New Physics searches at LHC using Anomaly Detection]

**Inês Moreira** · **Inês Ochoa** · **Nuno Castro** · **Rute Pedro**

## Motivation for New Physics searches

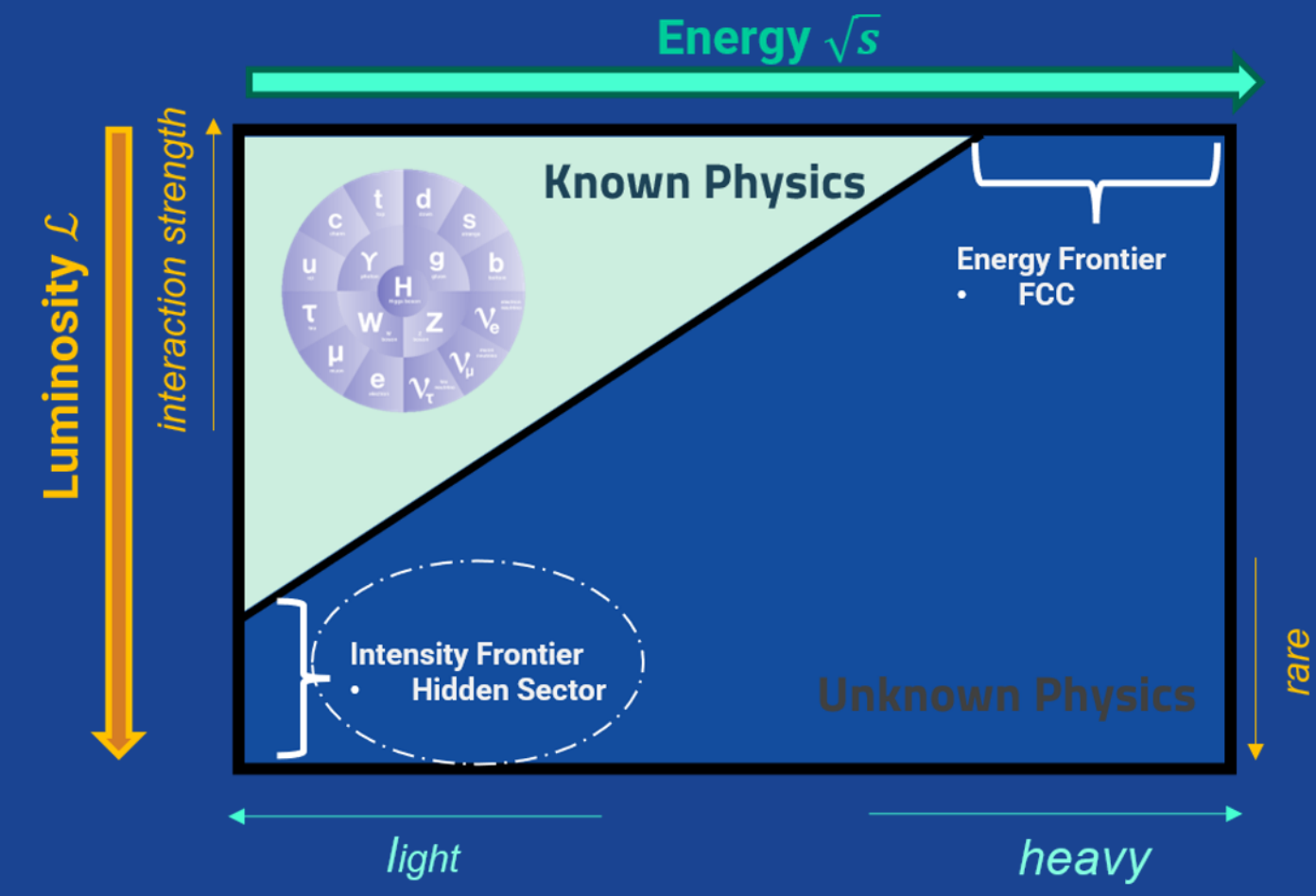**SM is not a complete theory** → **Phenomena not explained by SM**

- Dark Energy
- Higgs boson mass (quantum corrections)
- Dark Matter
- Neutrino masses and mixings
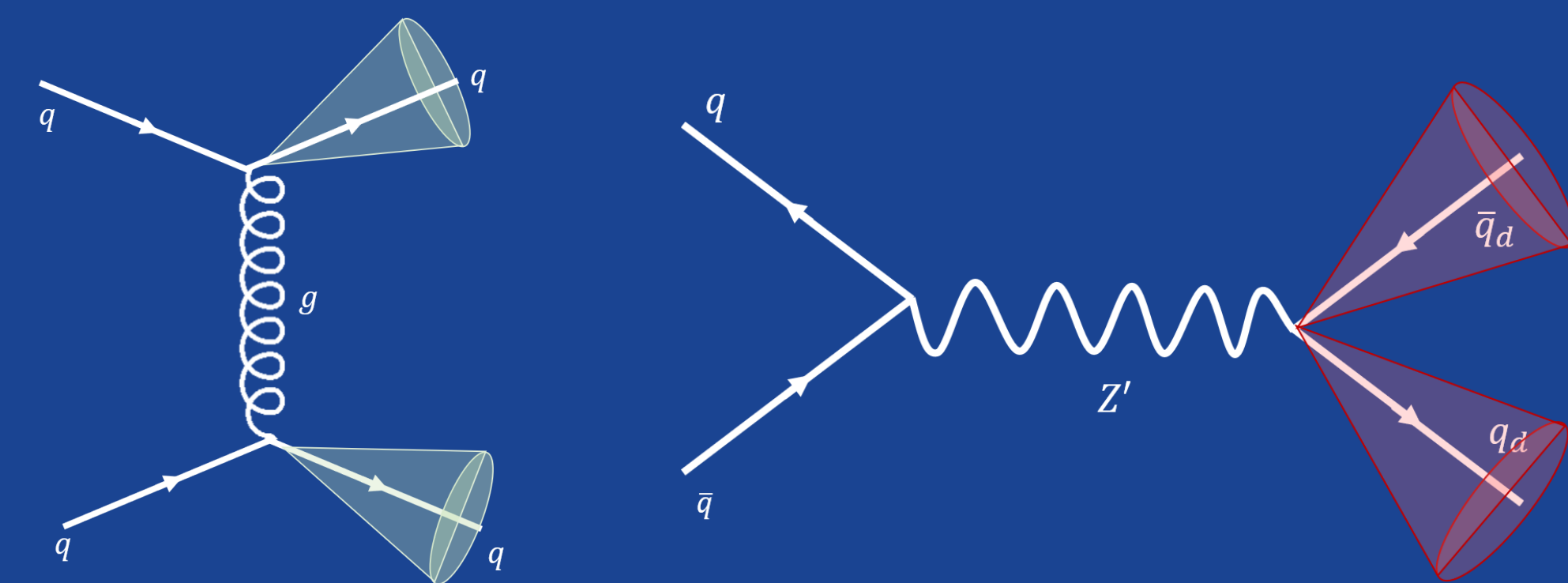- g-2 of the muon
- Baryon Asymmetry



**Anomaly Detection** methods will help us to find deviations from SM events without depending on specific BSM signals

- Assigns a score to an event depending whether it deviates from the main distribution or not
- Events with a low score are likely associated with the background, while those with higher scores are more likely to be signal events.

→ **BSM particles are too massive or produced with too low cross section**

or

→ **Current search program is not being sensitive to the regions of phase space populated by BSM physics.**

## AD at jet level:

↳ Finding anomalous jets

↳ We now know how to use jet constituents to identify different signals

↳ Jets are no longer required to serve as universal analysis objects (leverage various subjet features)



### Training

**SM background events**



**Model**

### Prediction

**Model** → **AD score** → 0 — 1

**Model** → **AD score** → 0 — 1

## Graphs:
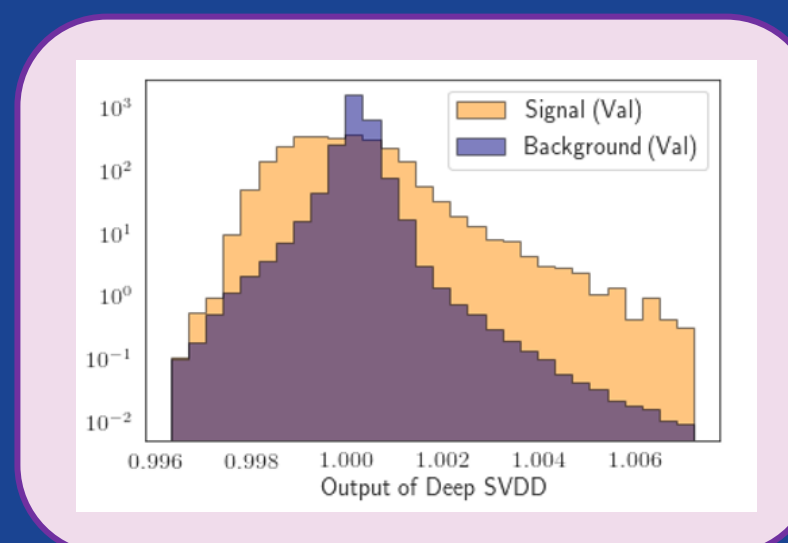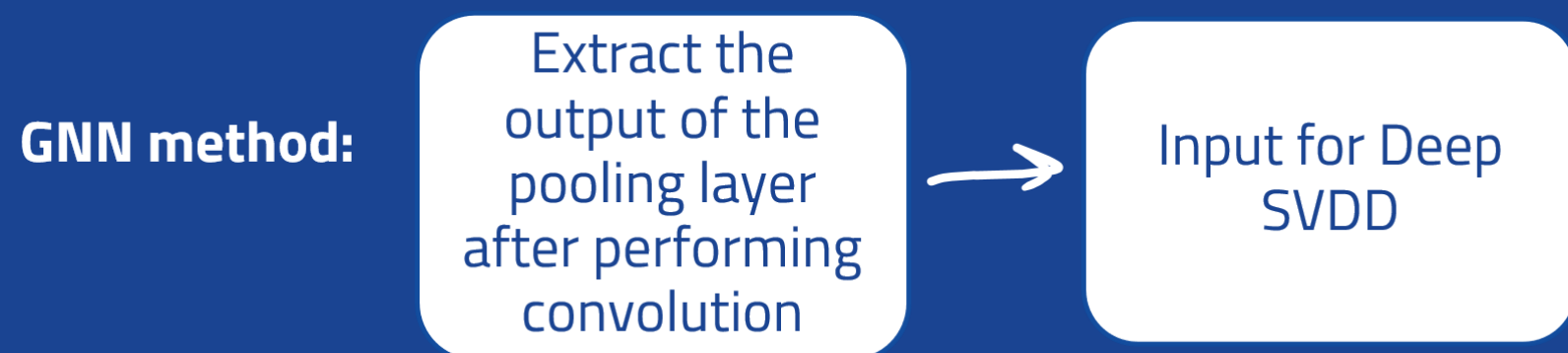
A graph represents the relations (edges) between a collection of entities (nodes). We can store information in each of the pieces of a graph trough nodes and edges embedding

## Graph representations of HEP data:

**Full event :** Nodes describe **physics objects** and the features of each node are the kinematic properties of those such as 4-momentum



Jet
MET
Jet
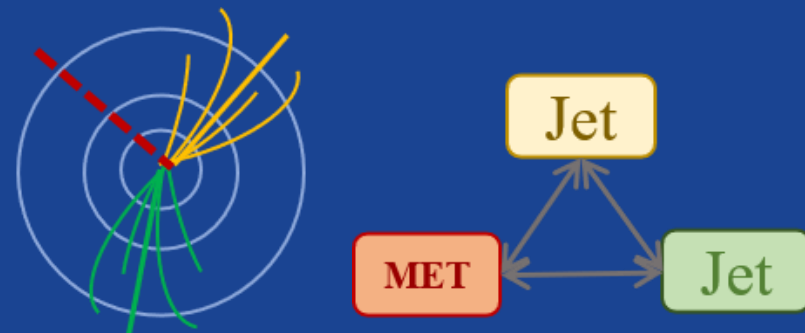
**Single jet:** Nodes describe **hadronic constituents** that were clustered into the jet



## Graph Neural Network (GNN) :

**Convolutions:**

**Node Aggregation**

**Edge Aggregation**



**Pooling:**

**Final Layer** — $U_n$ / $V_n$ — $\rho_{v_n \to u_n}$ — $c_{u_n}$ — **Global Prediction**

Pooling function $\rho$
Final classification $c$

**GNN method:** Extract the output of the pooling layer after performing convolution → Input for Deep SVDD



**Deep-SVDD:** → Unsupervised one-class classifier

↳ **Training** : Calculates the centre of the distribution of training events in the output space, and maps data points into this space learning the mapping that minimizes the distance from the centre.

**Test:** Background events will stay compact near the centre, while anomalous data points will be mapped far away.