# **Reconstruction of Long Lived Particles at CMS using graph neural networks**

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# Introduction: why long lived particles?

- Standard Model of particles doesn't answer all the questions about matter and interaction
- Extensions of SM predict partners of SM particles (SUSY), or dark sectors communicating with SM only via Higgs boson  $\rightarrow$  solves the Higgs mass divergences!
- Final state of interest: bb (predominant decay of Higgs)
- New particles are long lived: peculiar signatures in a detector @ LHC









### Introduction: LHC and CMS











- p-p collisions @ 40 MHz: fast decision  $\rightarrow$ sophisticated trigger systems
- CMS Particle Flow algorithm connects info from sub detectors → precise measurements of momenta and particle identification





# Introduction: LLPs signatures at CMS

- b-quarks: due to strong interaction, they hadronize in a jet of particles
- They are produced with a certain delay (lifetime ст) affecting the topology
- Decays in <u>tracker system</u>:
  - Tracks are displaced w.r.t. p-p collision point
- Decays in <u>calorimeters</u>:
  - Few tracks associated to a jet
  - Large **energy deposits** in **calorimeters**
  - Calorimeter crystals measure delay w.r.t.
     p-p collision









# Tracker lifetimes: why LLPs reconstruction is challenging



![](_page_4_Picture_2.jpeg)

![](_page_4_Picture_3.jpeg)

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![](_page_4_Picture_4.jpeg)

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### **Tracker lifetimes: displaced vertices with graph network**

- **Track**: collection of **hits**
- Ideal inputs for a graph network architecture!
- Graph construction:
  - One tracker hit per node (up to 1500 hits)
  - Features (per hit): x, y, z
  - Coordinates (per hit):  $\eta, \varphi$
- Adapt <u>ParticleNet</u> architecture to a regression problem:
  - MSE loss
  - No softmax

![](_page_5_Picture_10.jpeg)

![](_page_5_Picture_11.jpeg)

![](_page_5_Figure_13.jpeg)

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![](_page_5_Picture_15.jpeg)

# Tracker lifetimes: graph network results

![](_page_6_Figure_1.jpeg)

![](_page_6_Picture_2.jpeg)

![](_page_6_Picture_3.jpeg)

![](_page_6_Picture_5.jpeg)

### **Calorimeter lifetimes: graph network for displaced jet tagging**

- **Jet** interpreted as clouds of **PF constituents**:
  - First 25 jet constituents with  $p_T > 1$  GeV (points)
  - Points coordinates: euclidean distance ( $\eta$ ,  $\varphi$ ) as metric among *k*-nearest neighbours
  - Points features: energy, pT, charge, number of hits in tracker/pixel
- <u>ParticleNet</u> architecture:
  - Optimised k-nn and number of edge conv blocks
  - Additional shortcut to jet-level variables describing displacement (calorimeter time)

![](_page_7_Picture_8.jpeg)

![](_page_7_Picture_9.jpeg)

![](_page_7_Figure_10.jpeg)

• Training:

- Signal: jets matched to a LLP decay in calorimeter
- Background: inclusive SM processes, weighted with x-sec

![](_page_7_Picture_14.jpeg)

![](_page_7_Picture_16.jpeg)

# Calorimeter lifetimes: graph network performances

- Benchmark (blue dot): cut based approach, selecting jetlevel variables
- Red curve: ParticleNet using only jet constituents
- Light blue curve: ParticleNet with shortcut to jet-level variables
- At the same background rejection: 1.3 better signal efficiency (per-jet)
- Signal region: 2 tagged jets  $\rightarrow$  improvement by factor 1.8

![](_page_8_Picture_6.jpeg)

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![](_page_8_Figure_8.jpeg)

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## Calorimeter lifetimes: graph network results

- Impact of the graph net jet tagger: quantified with 95% CL exclusion limits
- Limits vs proper decay length
  - Graph network: improvement by a factor 2 w.r.t. cut based
- Perspectives:
  - Extend to heavier masses
  - Tweak the architecture, use more features for jet constituents

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![](_page_9_Figure_9.jpeg)

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![](_page_10_Picture_0.jpeg)

![](_page_10_Picture_1.jpeg)

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![](_page_10_Picture_21.jpeg)

## Graph network for tracker: details

Datasets:	Model perfo	
<ul> <li>Training: 27,942</li> <li>Validation: 9.314</li> </ul>	CN	
Test: 9,314	12	
Number of RecHits: 1500	11	
Training hyperparameters:	兴 10	
Optimizer: Adam	2	
Cyclic LR with:	9	
min = $5 \times 10^{-6}$ max = $10^{-4}$ step size = 10 epochs	8	
Number of epochs: 321	7	
Batch size: 72	0	

![](_page_11_Picture_2.jpeg)

![](_page_11_Picture_3.jpeg)

#### formance:

#### **MS** Work in Progress

![](_page_11_Figure_6.jpeg)

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