



End-to-End reconstruction using machine learning to search for exotic decays of Higgs



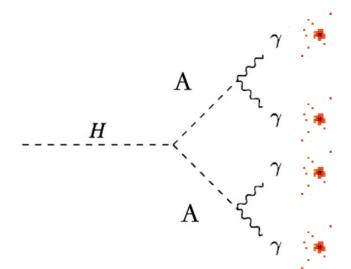
Shamik Ghosh (LLR Ecole Polytechnique - CNRS) Abhirami Harilal, Manfred Paulini (Carnegie Mellon University)

Probing exotic decays of Higgs

- → We probe using the newest discovered particle Higgs
 - Existing measurements leave room for BSM decays of Higgs

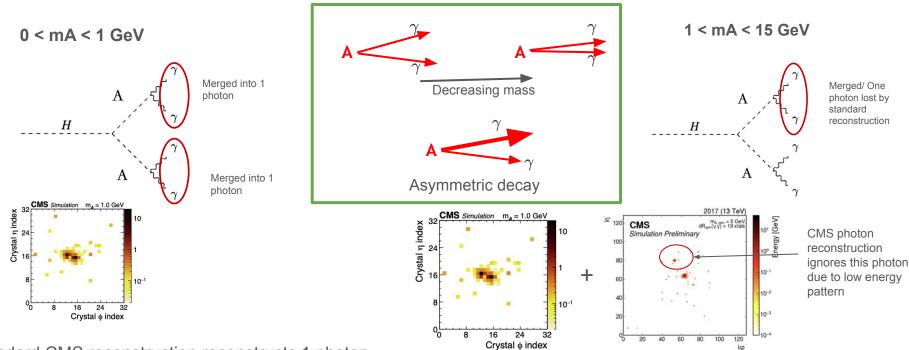
Br(H->BSM) ~ O(10%) allowed

- → H -> AA, A is a light scalar or pseudoscalar, well motivated in BSM models like 2-Higgs doublet (2HDM+S), Next-to-minimal SUSY (NMSSM), axion-like particle (ALP)
- → For low masses, photons offer a clean gateway



Probing exotic decays of Higgs

→ However, low mass creates challenges: Makes these invisible to us

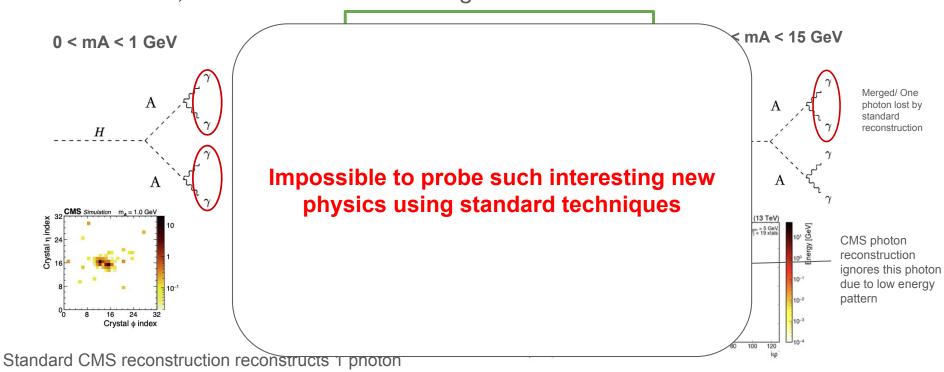


Standard CMS reconstruction reconstructs 1 photon per A 2 photon final state instead of 4 photons

Standard CMS reconstruction reconstructs 3 photon final state

Probing exotic decays of Higgs

→ However, low mass creates challenges: Makes these invisible to us



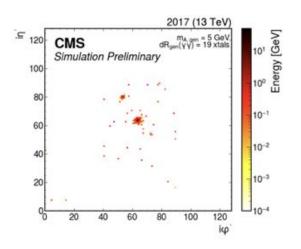
per A 2 photon final state instead of 4 photons

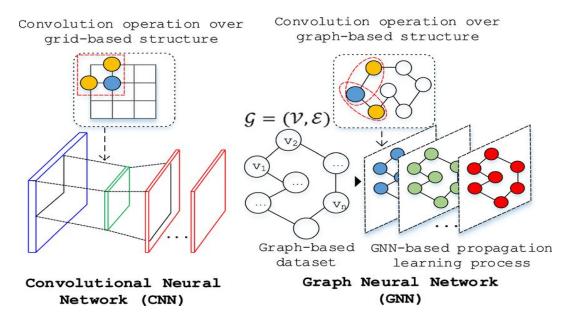
Standard CMS reconstruction reconstructs 3 photon final state

Moving to Graphs

Things are more complicated in the higher masses

- Both merged and semi merged
- Patterns over large detector area -> lot of sparsity
- Move from CNN to Graph Neural Networks





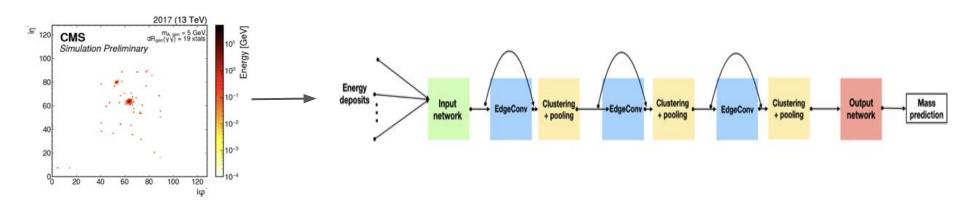
Novel Graph Neural Networks

A DYNAMIC REDUCTION NETWORK FOR POINT CLOUDS Particle property estimations using graph pooling (Dynamic Reduction Network) A PREPRINT Lindsey Gray, Thomas Klijnsma Fermi National Accelerator Laboratory Saha Institute of Nuclear Physics Batavia, IL 60510 Kolkata, West Bengal, India lagray@fnal.gov shamik.ghosh@cern.ch Coarsening / Pooling March 19, 2020 2003.08013 **Graph Properties** Coarse Input graph representation DGCNN graclus maxpool DGCNN graclus # nodes reduction

- Take in an unordered set and reduce to a vector of physically relevant quantities
- EdgeConv fused with clustering, learns best organization of input data to regress to desired properties

Training the reconstruction model

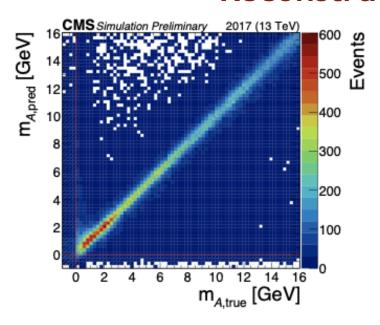
Perform Mass reconstruction from raw detector hits using DRN



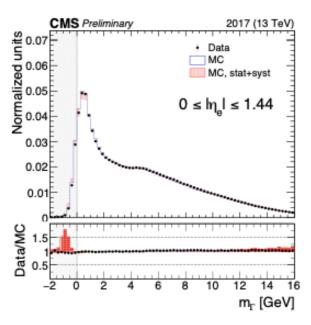
GNN is trained to predict mass of the system from raw hits (large dataset sizes!) Performs at the same time (End-to-End)

- Clustering of low energy photon
- Estimation of energy-momentum
- Energy corrections

Reconstruction Validation



The model nicely reconstructs masses over a wide range



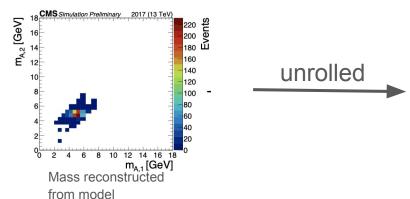
Model response in simulation compared to Z to electron decays in data

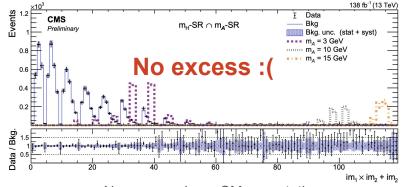
Model is also trained with single photons with mass mapped to [-3,0]

standard photons

Final Result!

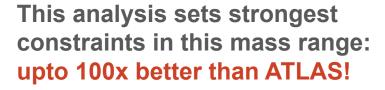
CMS





No excess above SM expectation

13 TeV

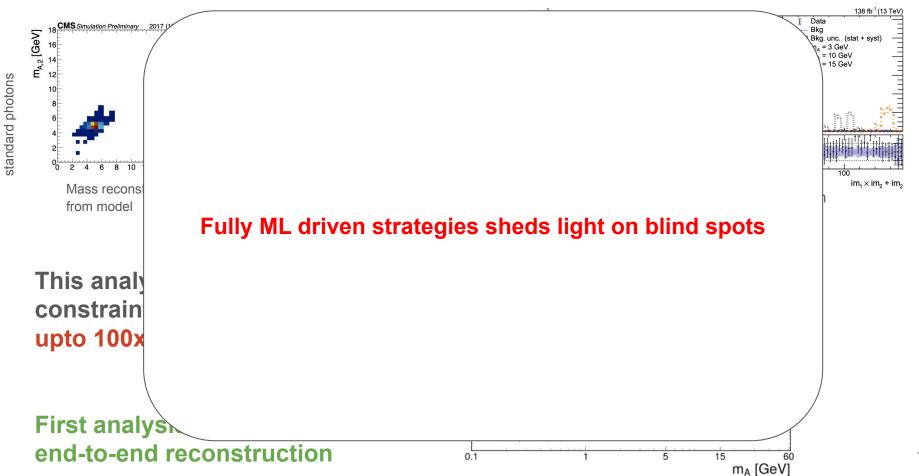


4γ) [pb] 95% CL upper limits Observed Ower is betterpected (± 2σ) sensitivity - H) × B(H ↑ CMS semi-merged CMS fully-merged dd) σ 10-4 CMS fully-resolved ATLAS Eur. Phys. J. C 84 (2024) 742 m_A [GeV]

CMS-PAS-EXO-24-025

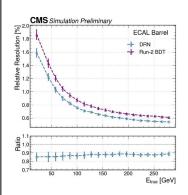
First analysis using GNN end-to-end reconstruction

Final Result!

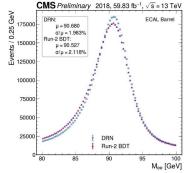


Further Applications

CMS ECAL Calibration

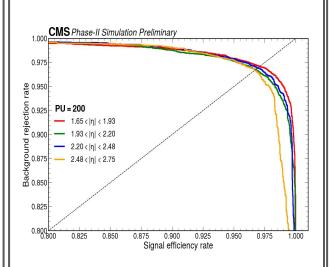


GNN based regression improves energy resolution



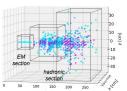
GNN based regression improves mass resolution

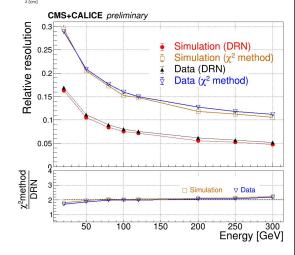
HGCAL PID



GNN based photon tagger performs well in 200 PU

HGCAL Hadron Reconstruction





GNN based pion reconstruction improves energy resolution

Summary

- → Detectors preserve signatures of hard to find signs of new physics
 - Optimised ML strategies essential to reconstruct them

→ Novel GNN developed to recognise patterns in granular detectors

→ Developed method leads to significant improvements in BSM physics reach

Read more:

https://cms.cern/news/one-photon-short-recovering-lost-photons-using-ai-hunt-ex otic-higgs-boson-decays

Thanks for listening!

BACKUP