Advanced deep neural networks for high-granularity calorimeters.

Jan Kieseler

29.01.2020

Outline

- Short introduction
- Exploiting shower shape variables
- Using hits in regular geometries
- Irregular geometries
- Seedless inference

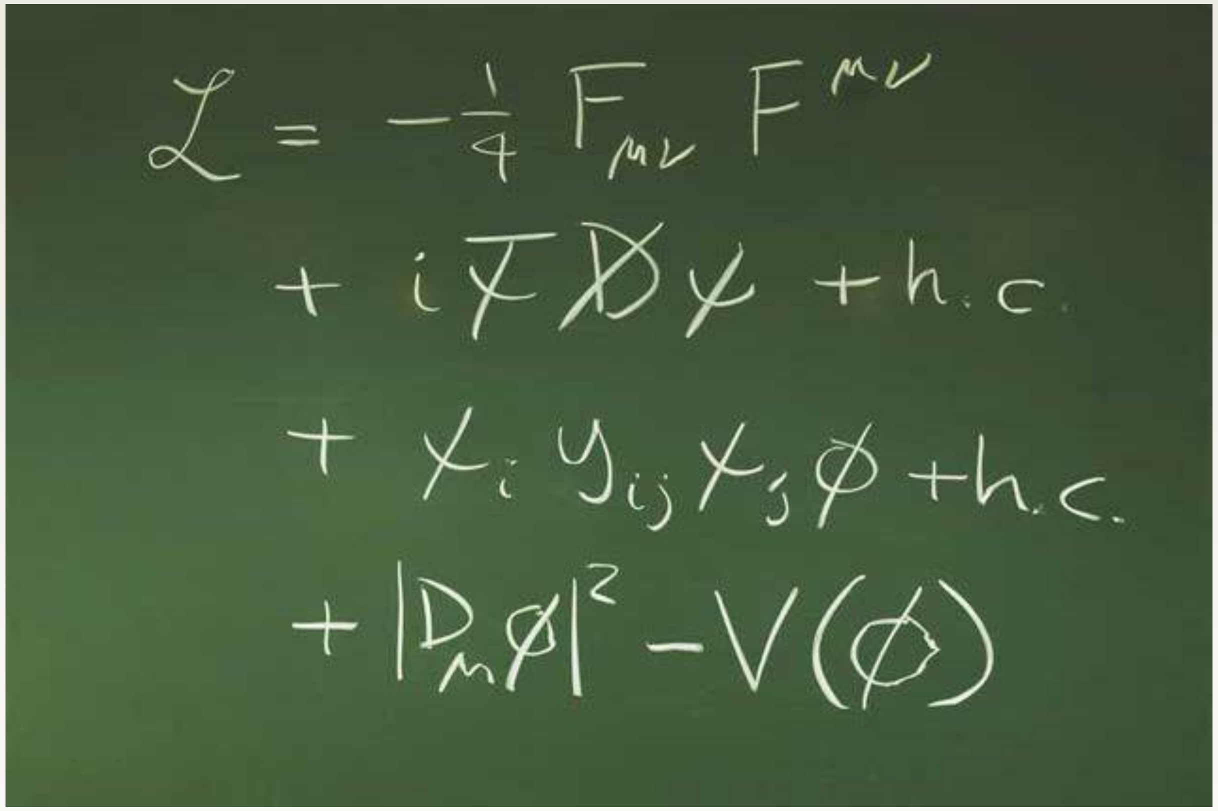
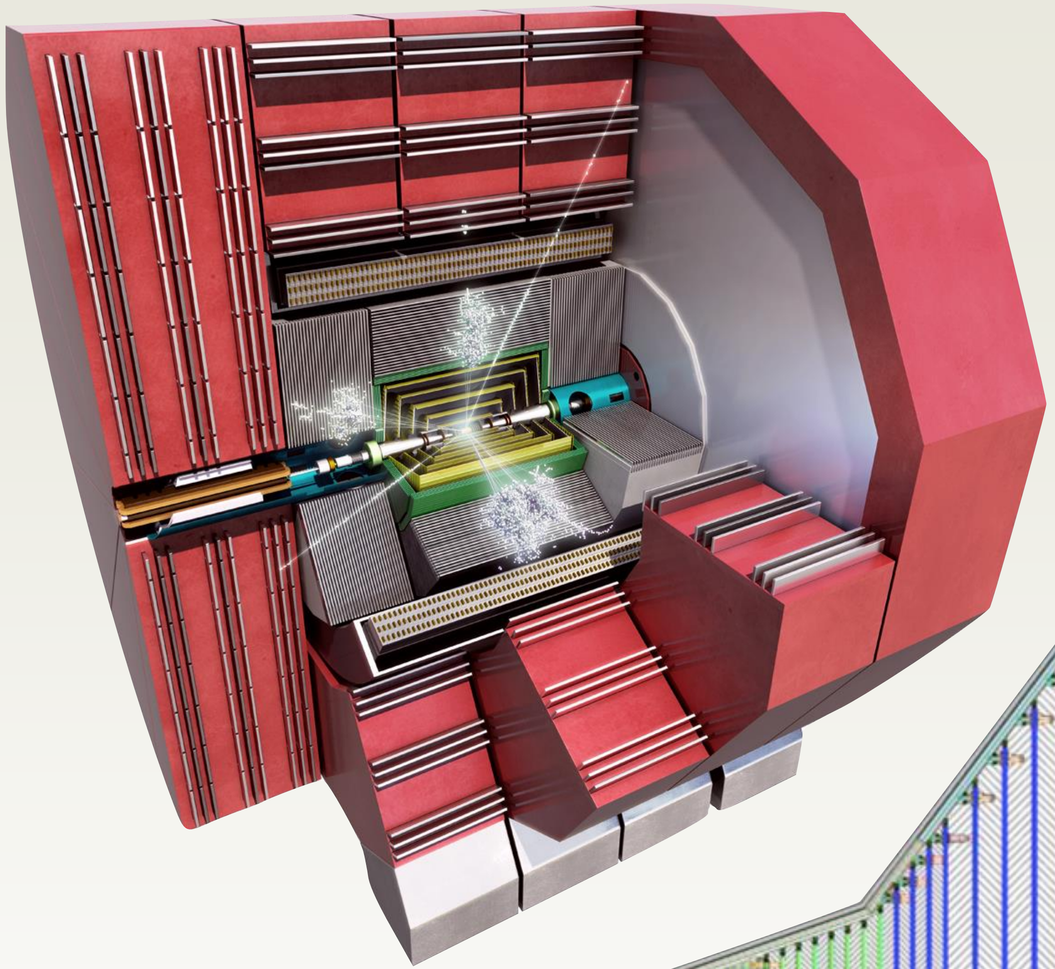
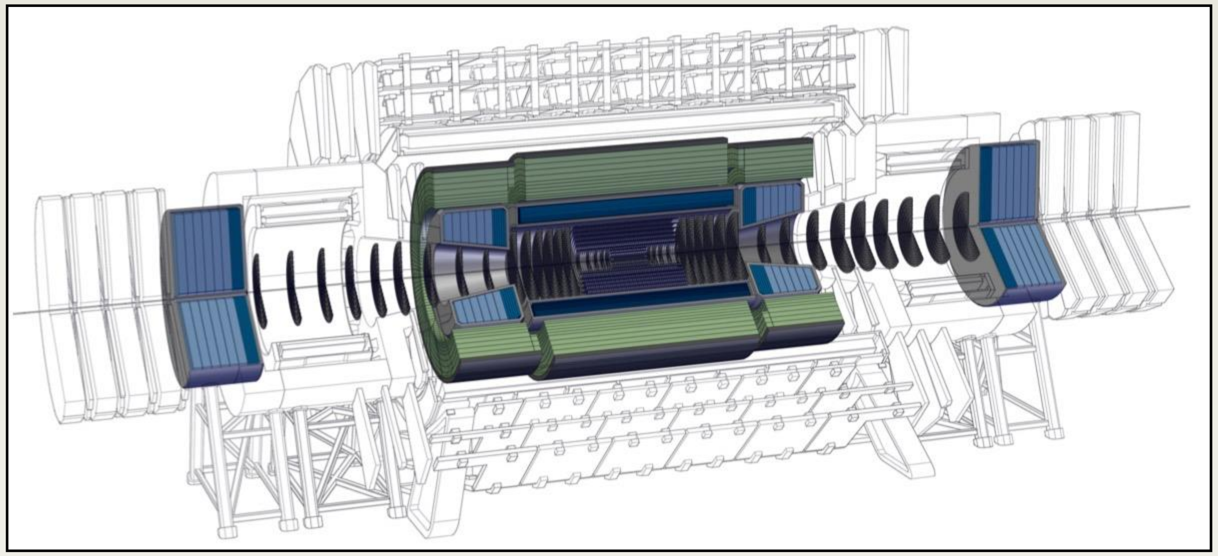


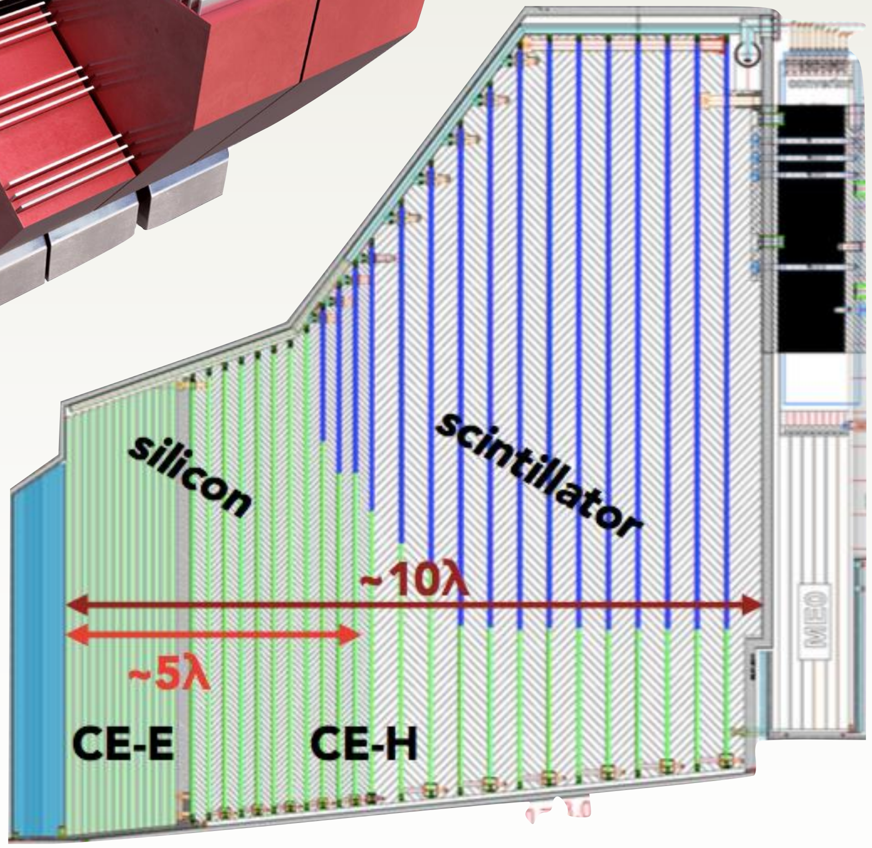
Image search using this talk's title

- *More focus on techniques than on calorimeters or results*

High granularity calorimeters





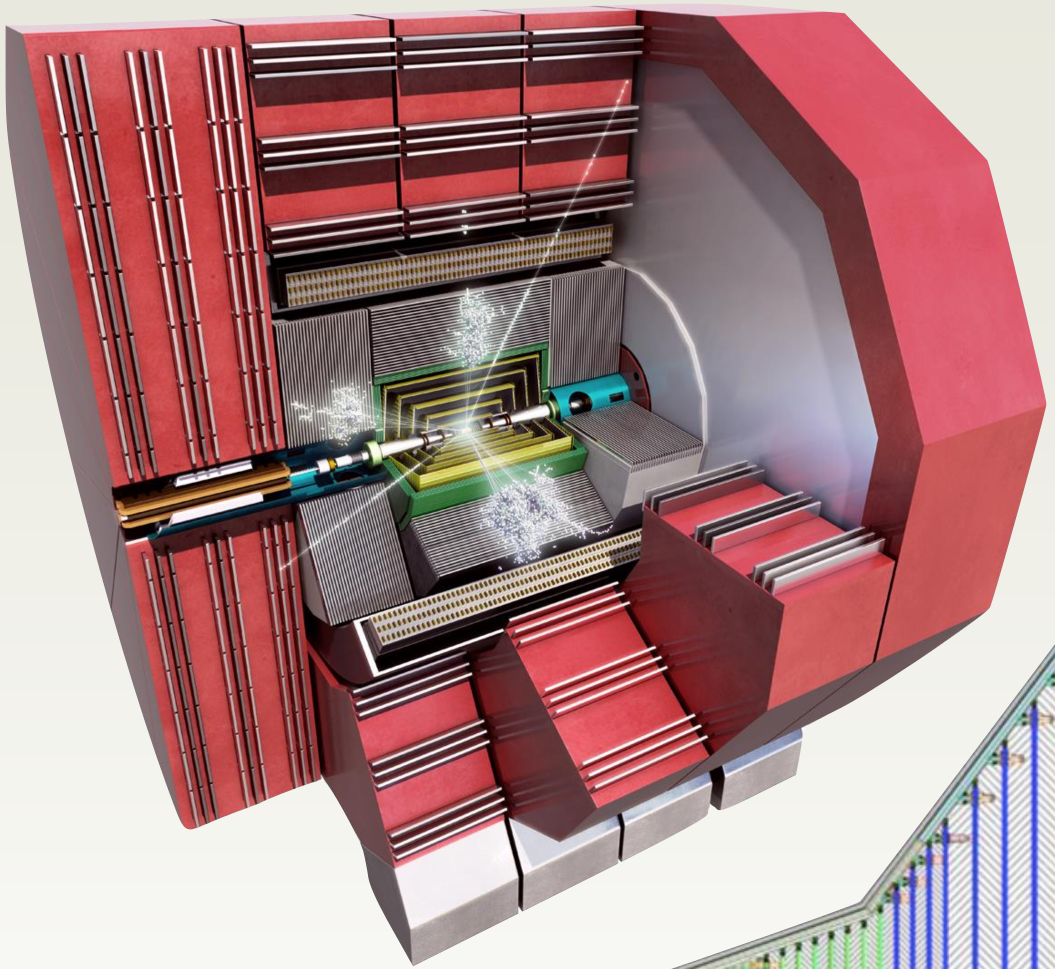


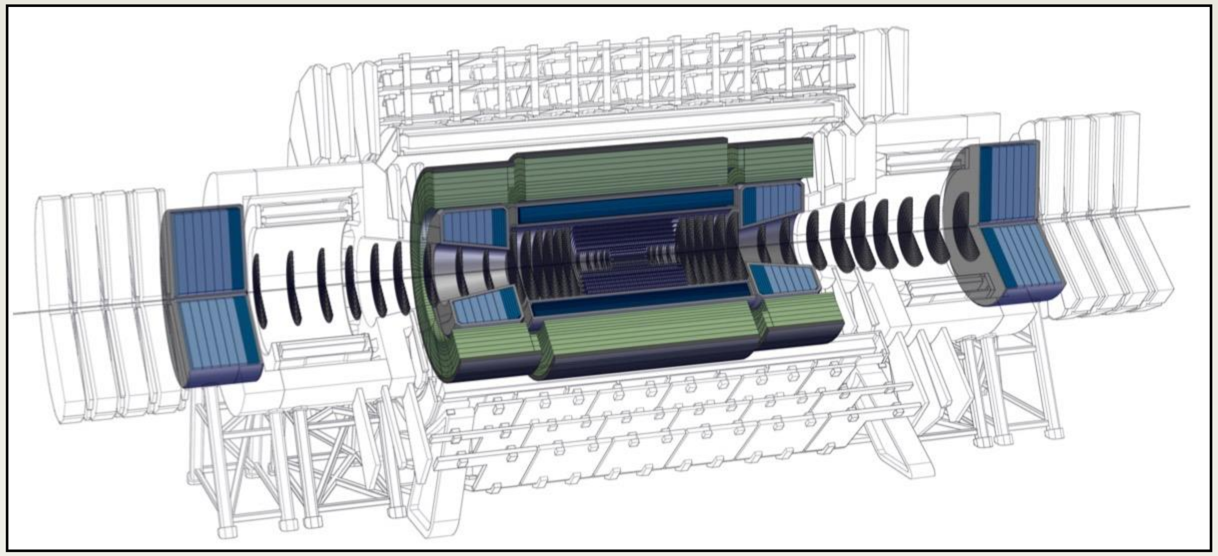
CALICE, FCChh (barrel), CMS HGCal

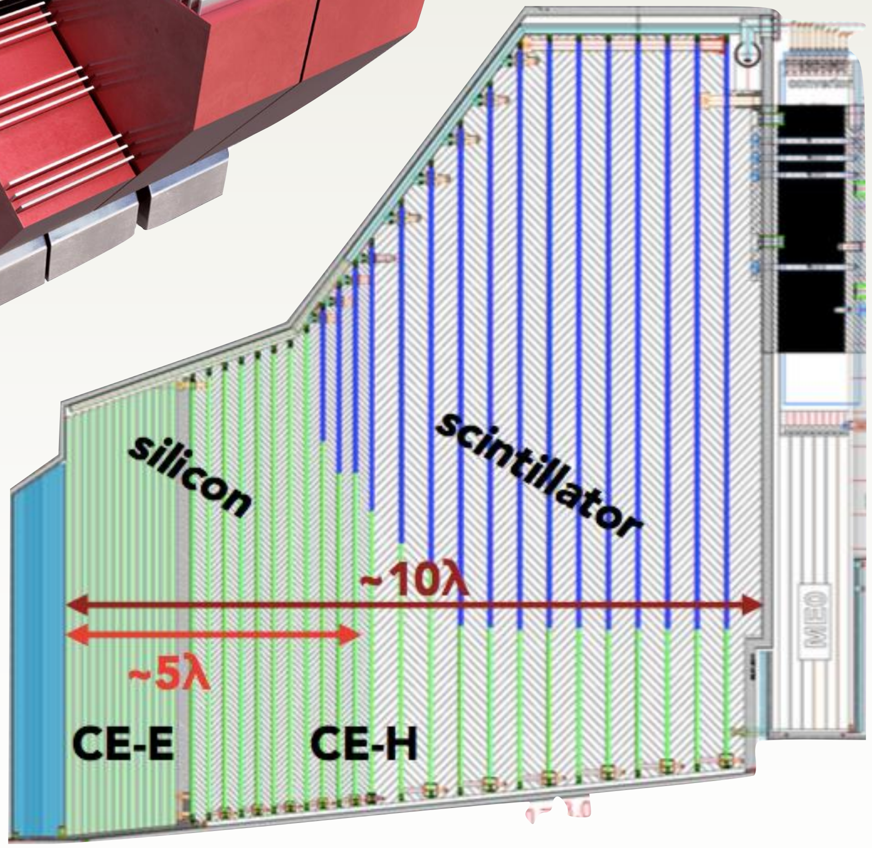
- In parts very different concepts
  - LAr,
  - Si (+SiPM)
  - SiPM
- However similar granularities
  - About 1cm x 1cm transversal (ECal)
  - > 10 layers longitudinal

M. Aleksa: https://indico.cern.ch/event/838435
F.Simon: https://indico.cern.ch/event/838435
CMS TDR 17-007

High granularity calorimeters







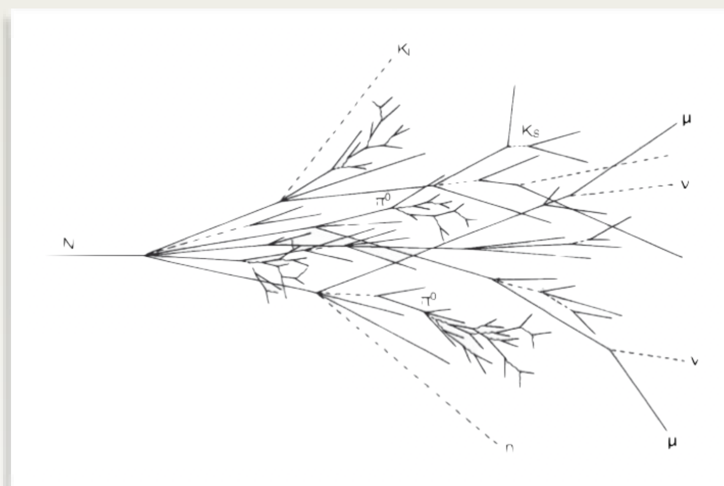
- Handle Pileup
  - 200 (CMS) - 1000 (FCChh)
- High precision energy measurements
  - Missing energy/precision resolution
- Fully consistent Particle Flow
- Particle ID
  - Also part of software compensation
- Fully utilise timing

- Similar w.r.t. basic reconstruction concepts

Calorimeter Reconstruction

Energy reconstruction

Particle
Flow, pileup
suppression

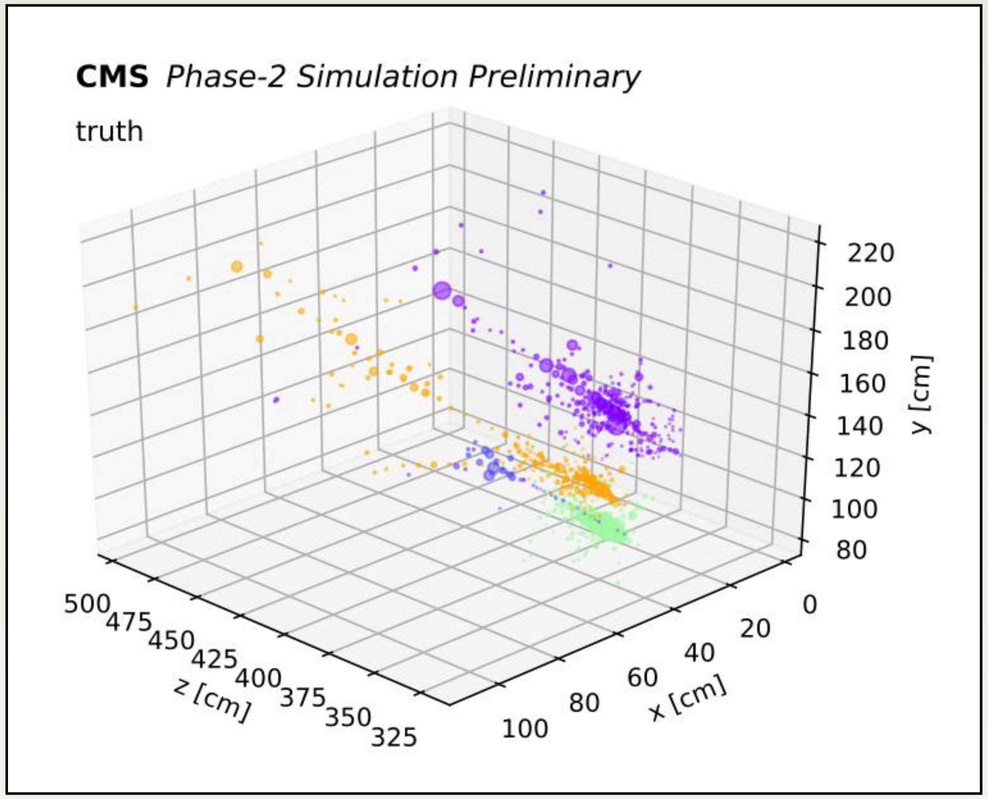


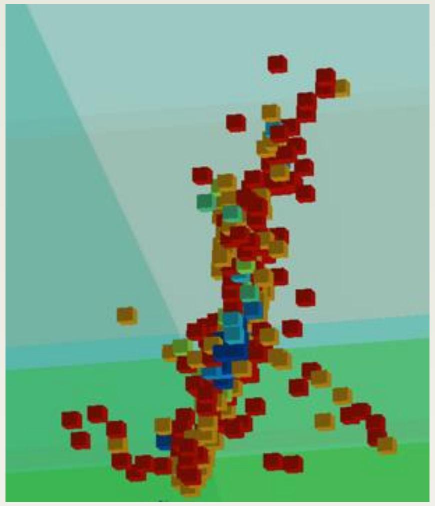
Software
Compensation
etc

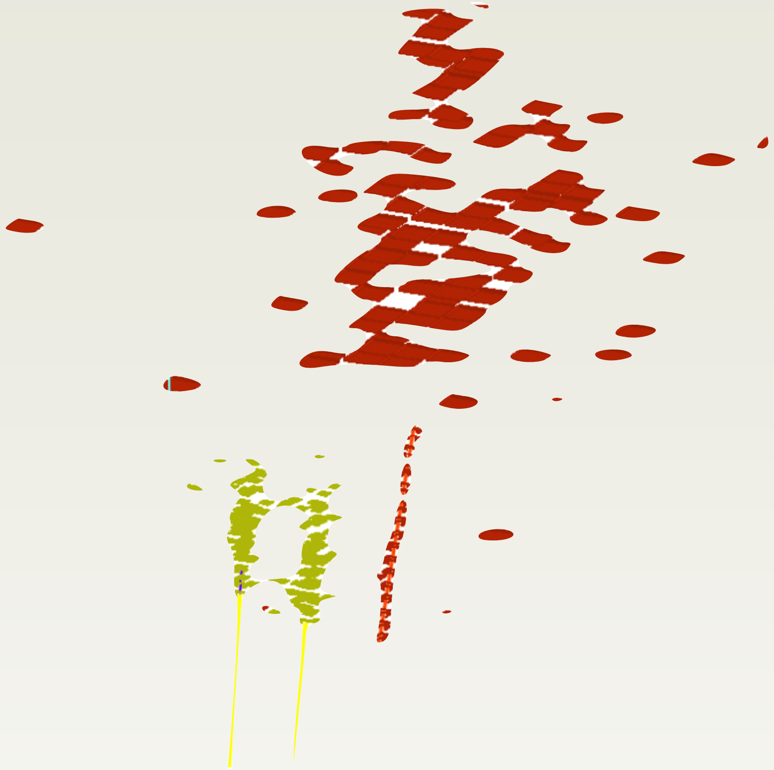
Shower separation

Shower identification

HG calorimeters and ML



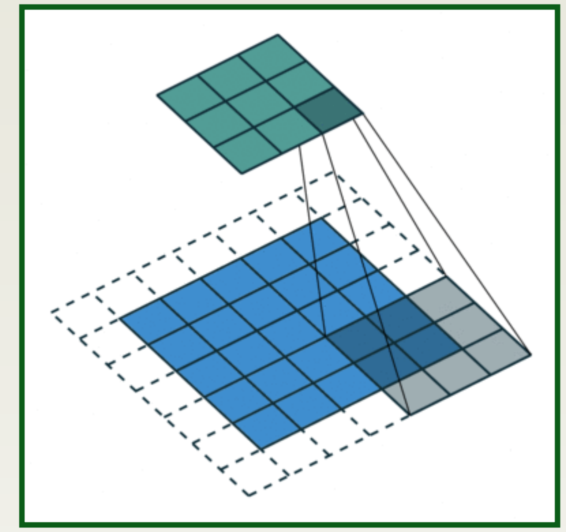




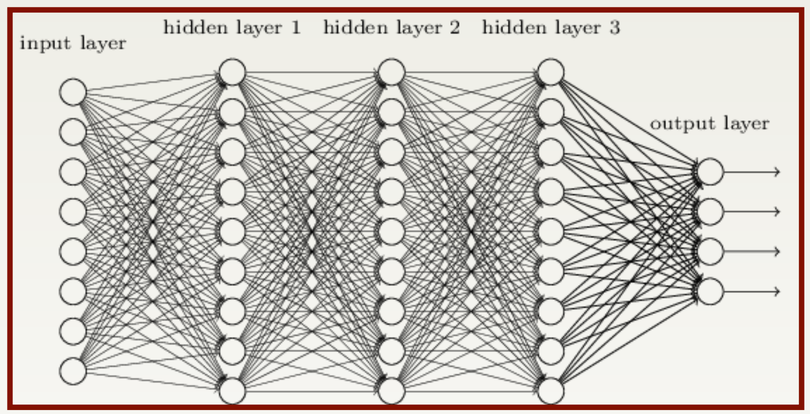
- High granularity calorimeters produce 3D/4D images of showers
- Deep neural networks have made many advances possible in the last years
  - Image classification, face recognition, …., self-driving cars, …
  - More and more applications in HEP (jet-tagging,…)
- Very powerful where 'things get messy’: e.g. real cows versus spheric cows in vacuum

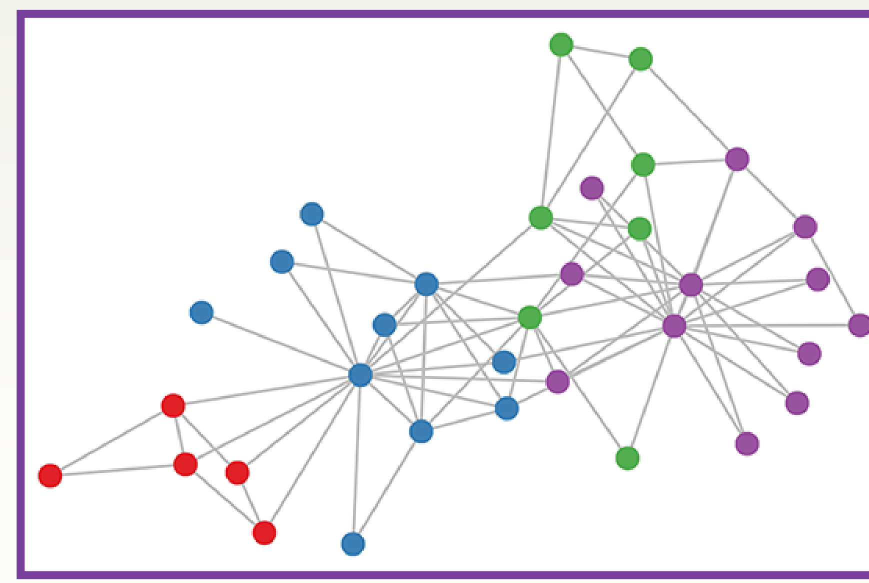
Basic DNN building blocks

- Three off-the-shelf DNN types / building blocks
  - Fully connected 'dense' (very powerful but many parameters)
  - Recurrent ('time' series, good for sparsity, less parallelisable)
  - Convolutional (translation invariant structures, *key to image processing*)

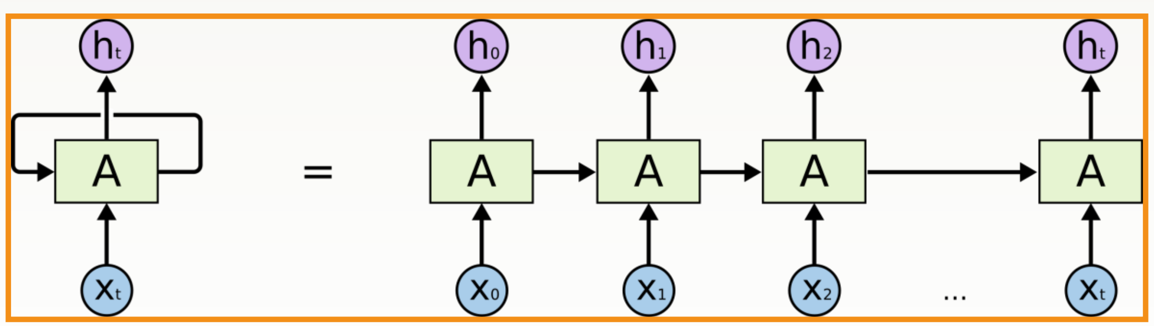


- Rather recent developments: Graph neural networks
  - Will cover details later





- All mostly matrix multiplications
  - Fast and parallelisable
- Approximate an unknown function: *structure is the key!*

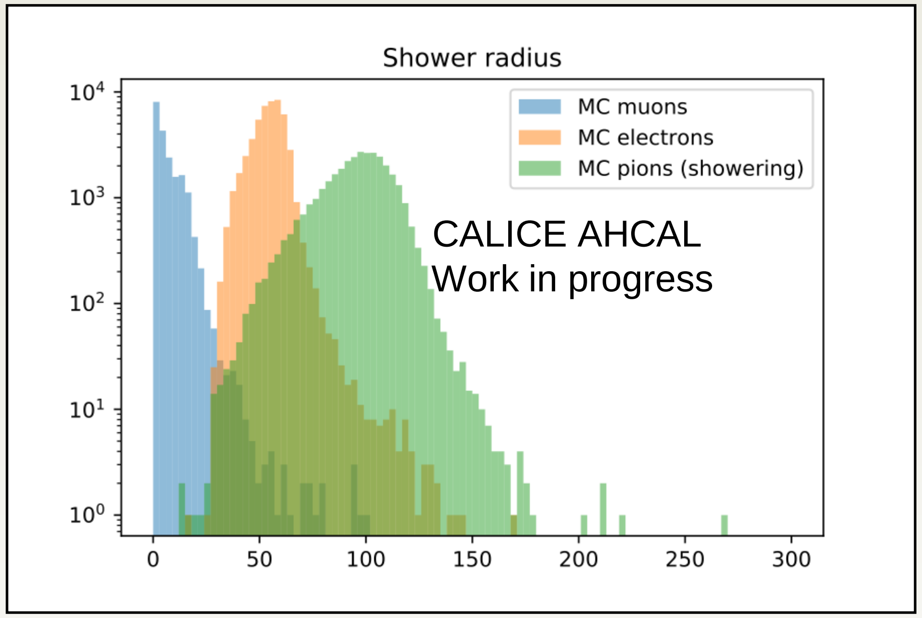


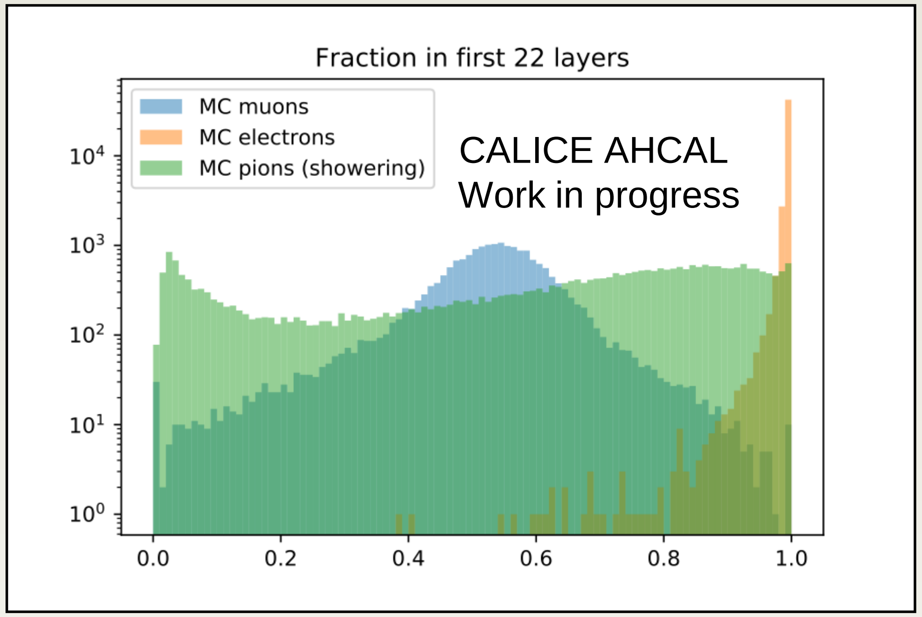
- Trained by minimising a loss function

Adam: D. Kingma, J. Ba, arXiv:1412.6980, conf. paper
AdaGrad: J. Duchi, E. Hazan, Y. Singer (2011)
RMSProp: T. Tieleman, G. Hinton (2012)
Stochastic gradient descent: H. Robbins; S. Monro (1951)

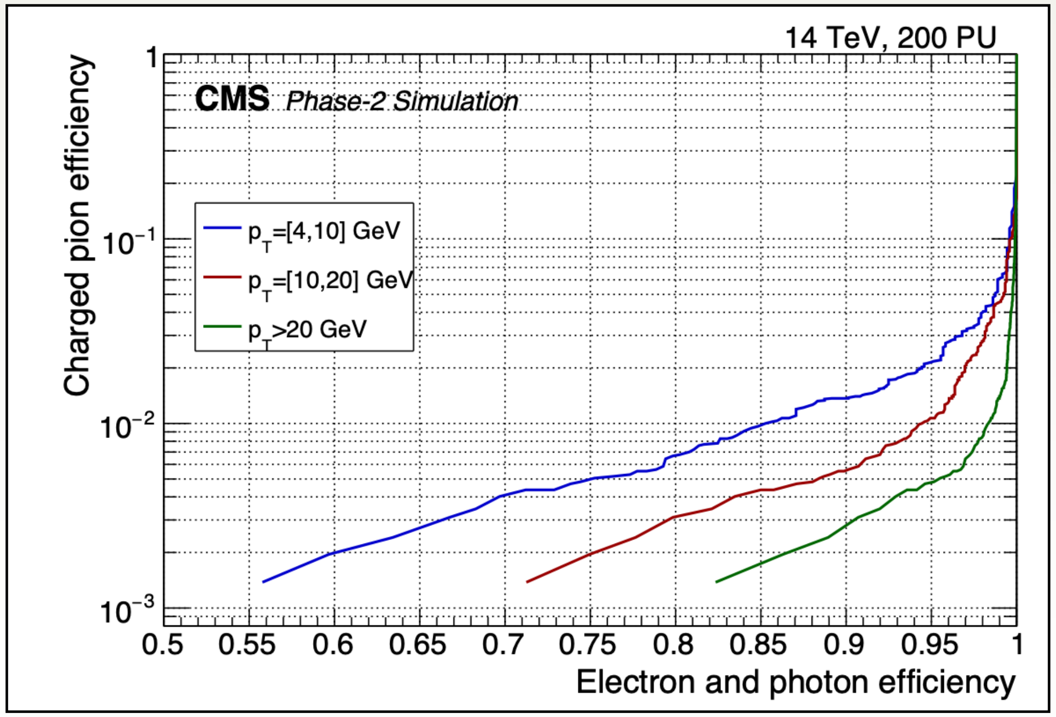
Particle Identification

- Most important: separate EM showers from hadronic showers
  - Utilise global shower shape variables





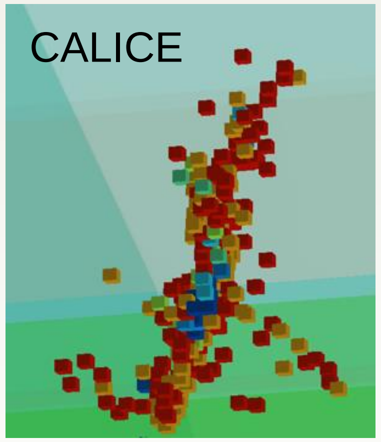
  - Process *individual hits* with DNNs based on off-the shelf convolutional layers as used for computer vision

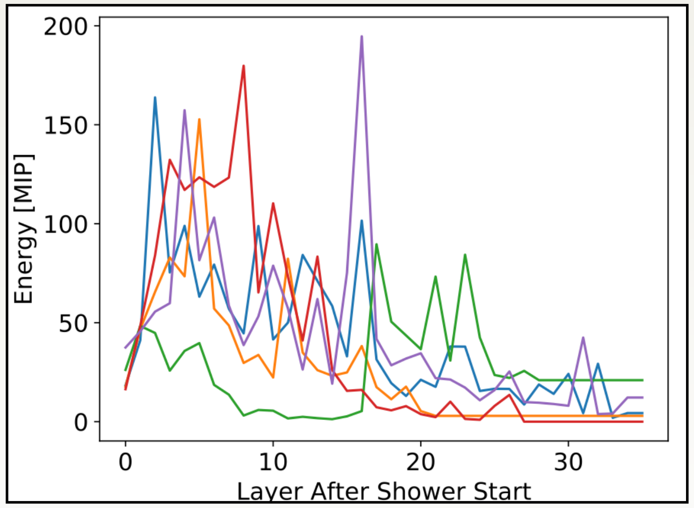


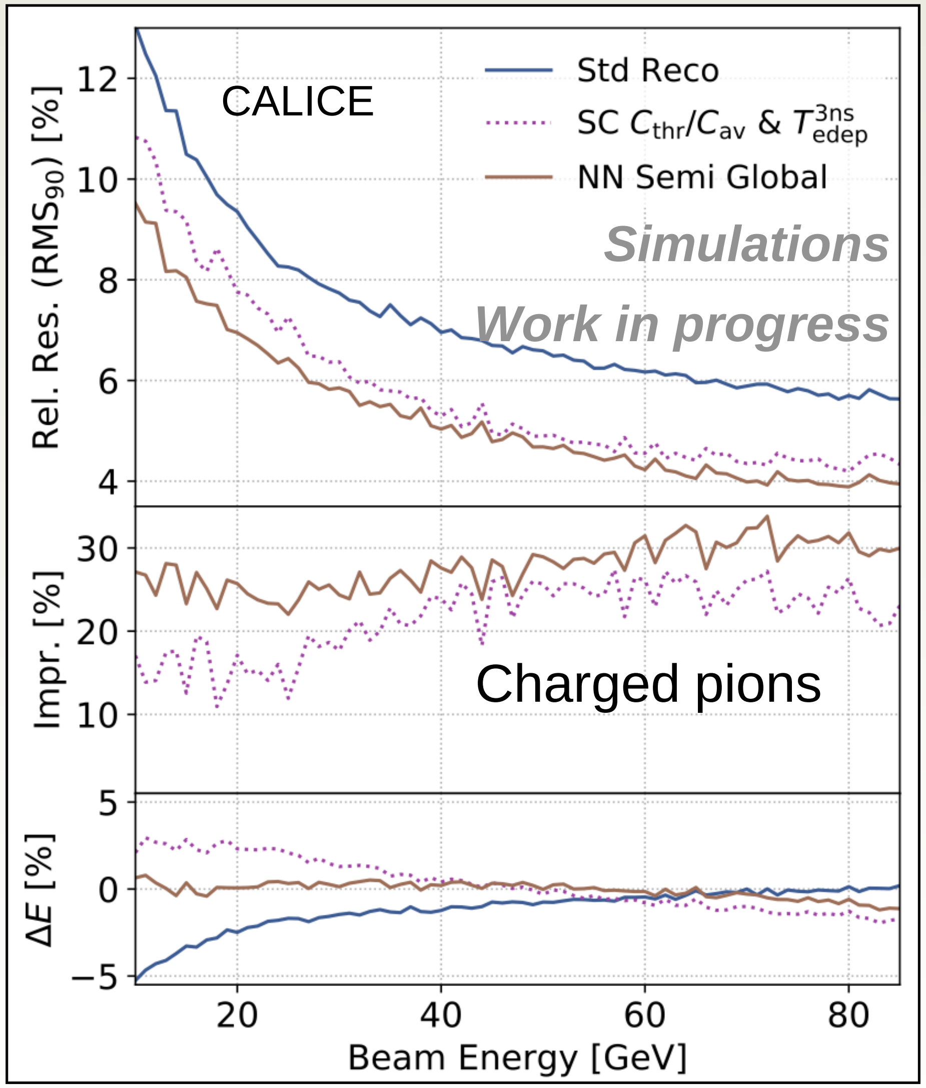
- High performance particle classification even in high pileup environments is possible already using off-the shelf architectures

Plots: V. Bocharnikov, CMS TDR-17-007

- Separate electromagnetic and hadronic components
  - Strongly increased resolution for hadron showers
- Human engineered:
  - weight EM components less than hadronic components
  - Identify EM components by local energy density







- Machine-learning based
  - Consider shower shapes, in particular longitudinal
  - Feed in dense NNs

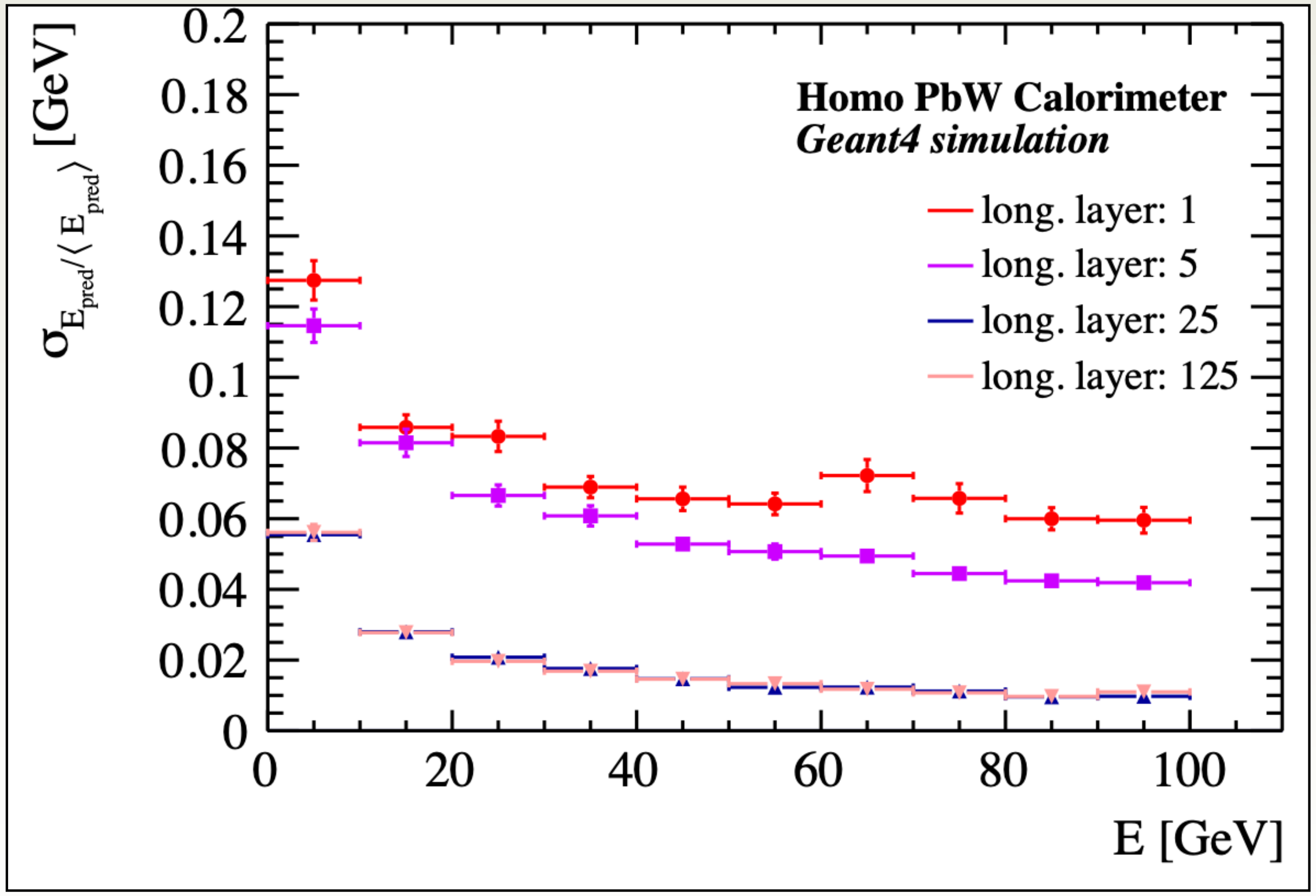
plots: C. Graf

Software compensation

- How does calorimeter segmentation impact software compensation
- Turn it around: use DNN as a tool for (almost) optimal reconstruction

- Consider lead tungsten calorimeter
  - Factorise out sampling and electronics effects
  - 1m x 1m x 2.5m
  - *10 λ , 200 X_0*

- Compare different longitudinal segmentations
  - 10 λ
  - 2 λ ~ 40 X_0
  - 0.4 λ ~ 8 X_0
  - 0.08 λ ~ 1.6 X_0



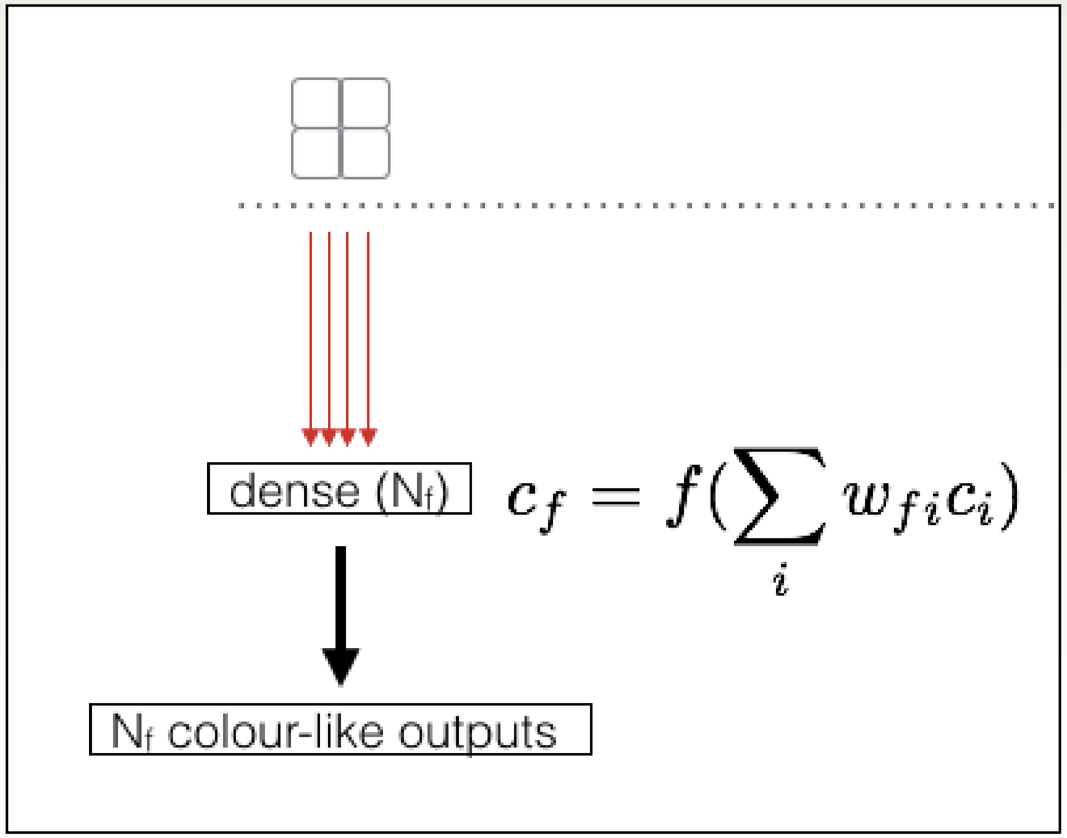
- Resolution saturates between 2 and 0.4 λ for full energy range

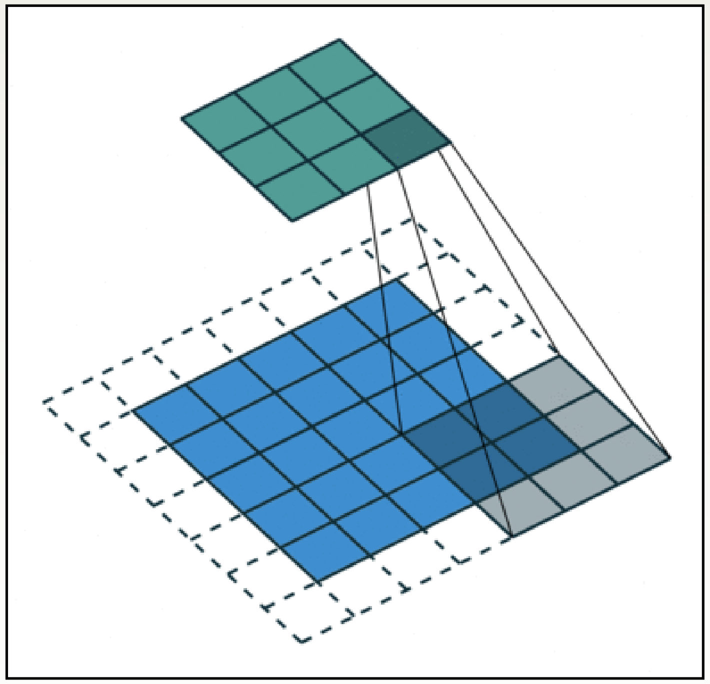
C. Neubüser, JK, paper in prep.

Exploiting more granularity

- Showers in calorimeters are similar to images

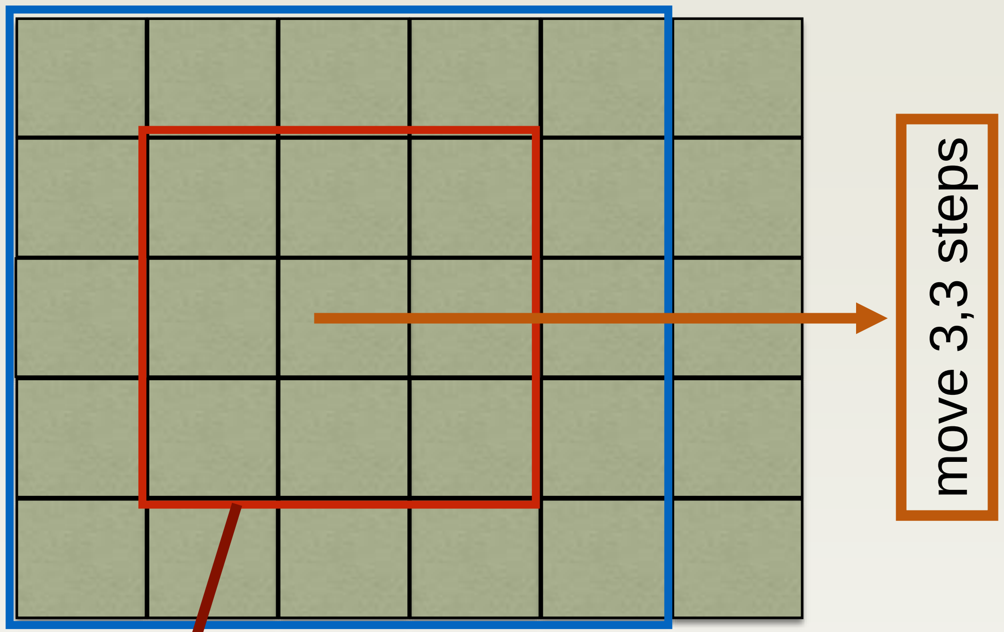
- *However*, energy determination is very different from shower classification
  - Determine energy: one obvious 'good' choice: energy sum: weight = 1
  - Classify: omit large weights, usually correlated to overtraining





- Need to develop dedicated CNN-like structure

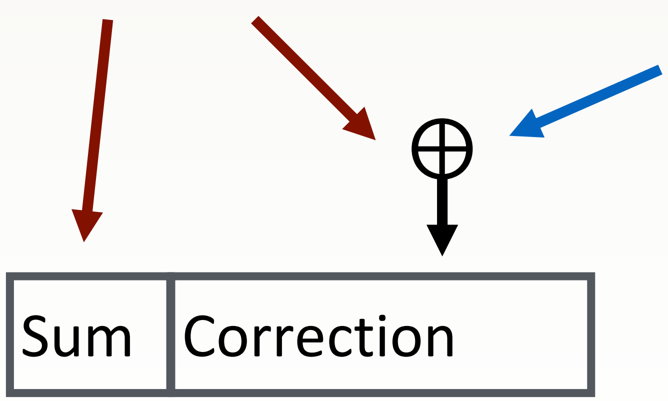
Dedicated CNN structures



"direct" block:
non-overlapping kernels + feed-forward sum

"correction" block:
- overlapping kernels,
- more nodes, more internal layers, *non-linearities*
- initialised with small weights

Regularised



- Apply to charged pion showers in FCChh barrel calorimeter
  - HCal: 17x17x10x2
  - ECal: 34x34x8x2 → 17x17x8x8
- In total 4 blocks with different kernel sizes

Calo-Resnet direct: (2,2,1) correction: (3,3,2), (2,2,3)
Calo-Resnet direct: (4,4,1) correction: (4,4,2), (2,2,3)
Calo-Resnet direct: (1,1,3) correction: (3,3,2), (2,2,4)
Calo-Resnet direct: (2,2,3) correction: (3,3,3), (3,3,3)

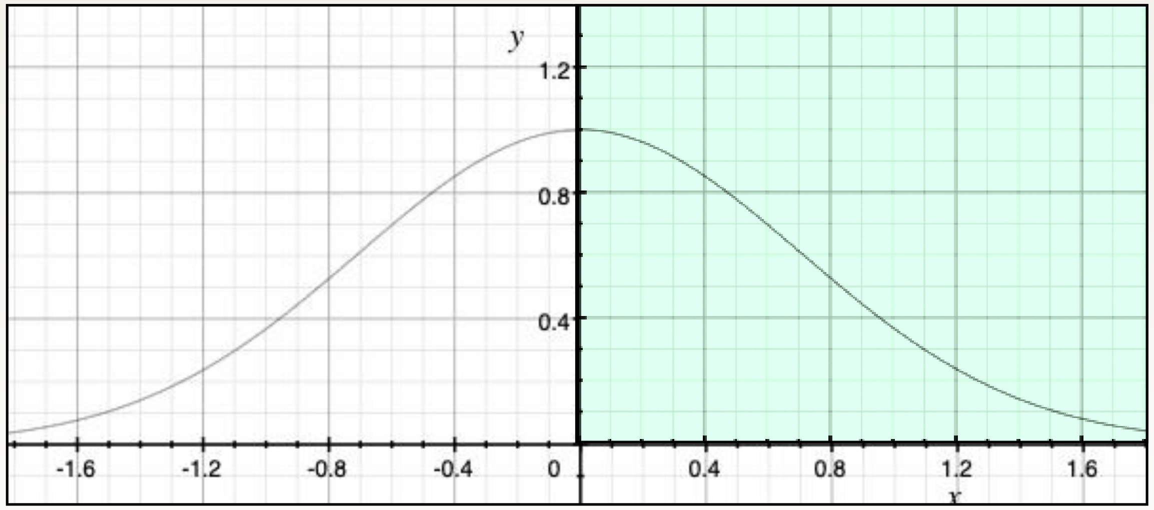
- Dense layers → energy

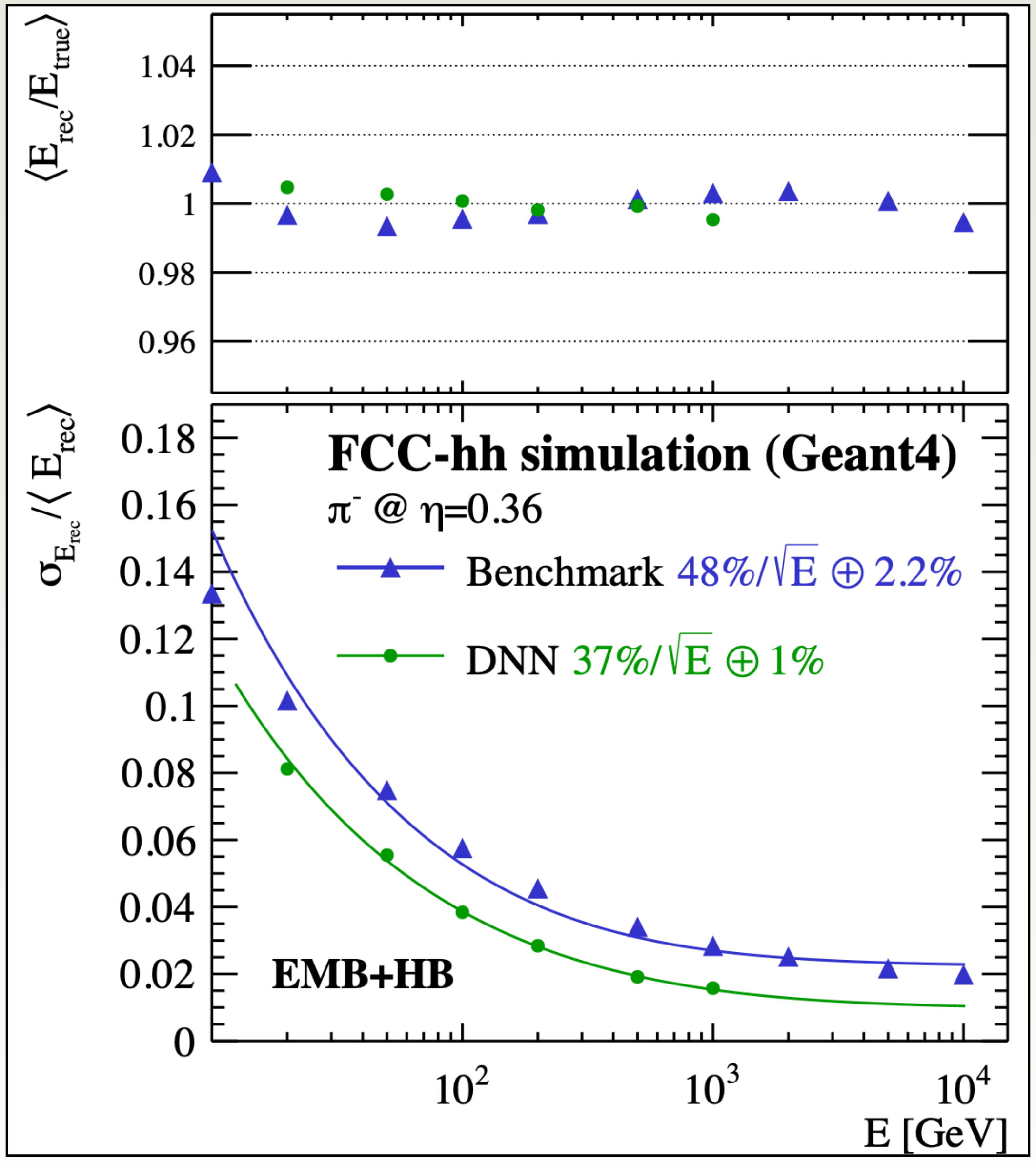
Resnet [1] inspired, [1] K. He, arxiv:1512.03385

C. Neubüser, et al, arXiv:1912.09962

Results and linearity

- High gain from ML based approach
- Sampling term of only 37%
- Linearity at edges not optimal → *very common*
  - Network learns quickly: E>0
  - Expectation value and mean differ

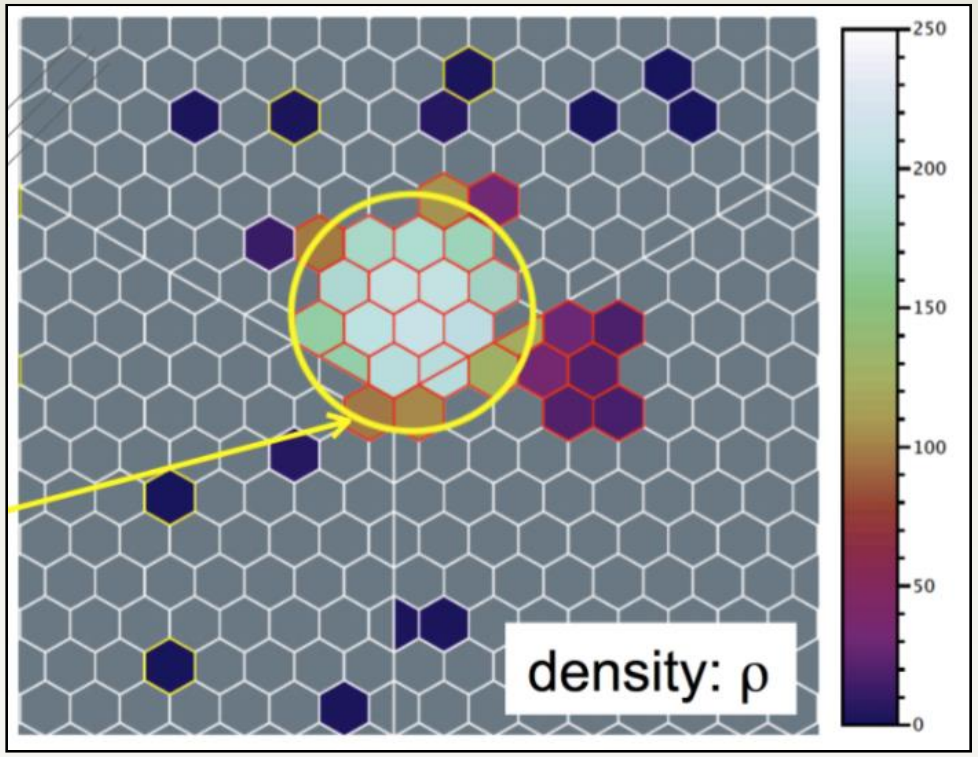


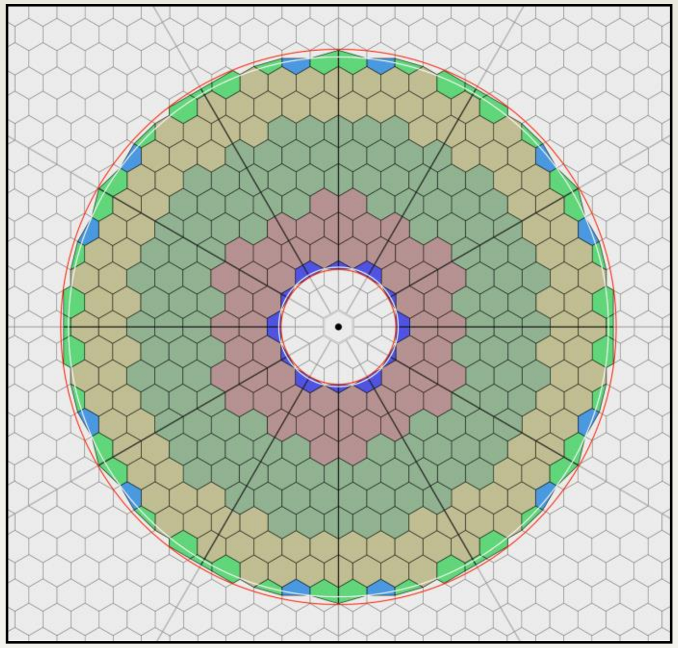


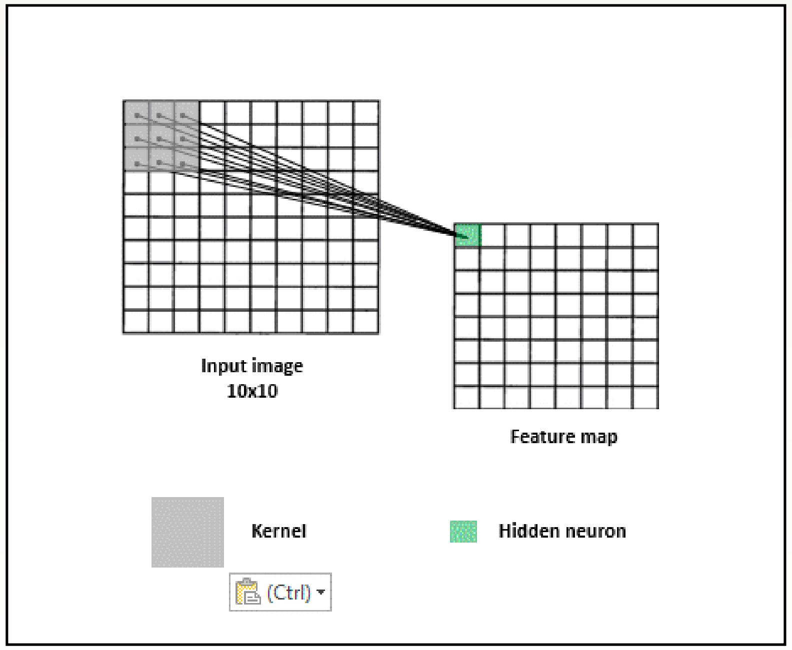
- Solution
  - Add global correction layer
  - In the last iterations, fix the rest
  - Train correction layer using randomly chosen bins to minimise <E>-<E_{true}>

C. Neubüser, et al, arXiv:1912.09962
More details will be in C. Neubüser, JK, paper in prep.

Going beyond regular geometries







- Detectors are not regular grids
- E.g. CMS HGCal
  - Hexagonal sensors
  - Size changes with depth and η

Representation of showers

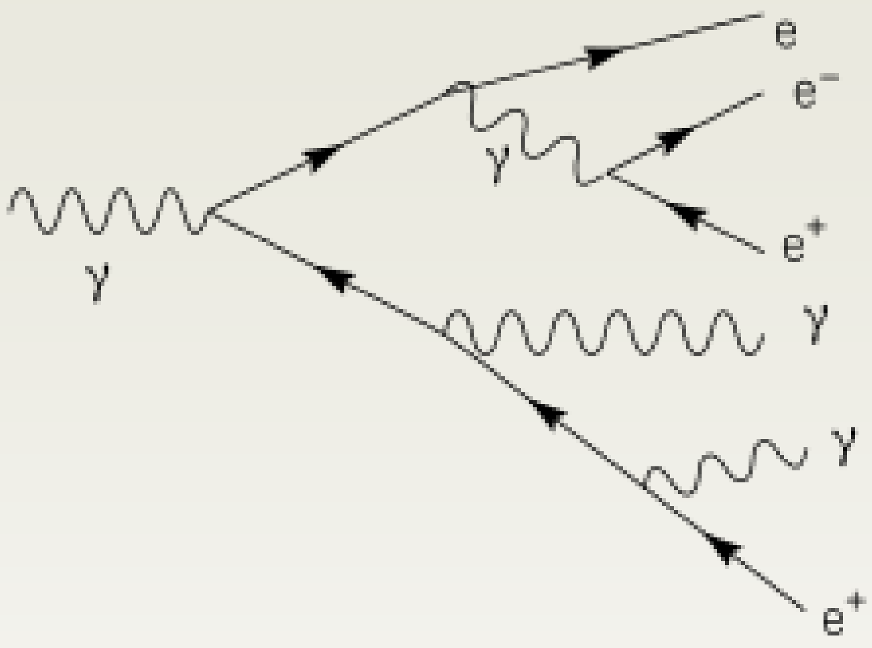
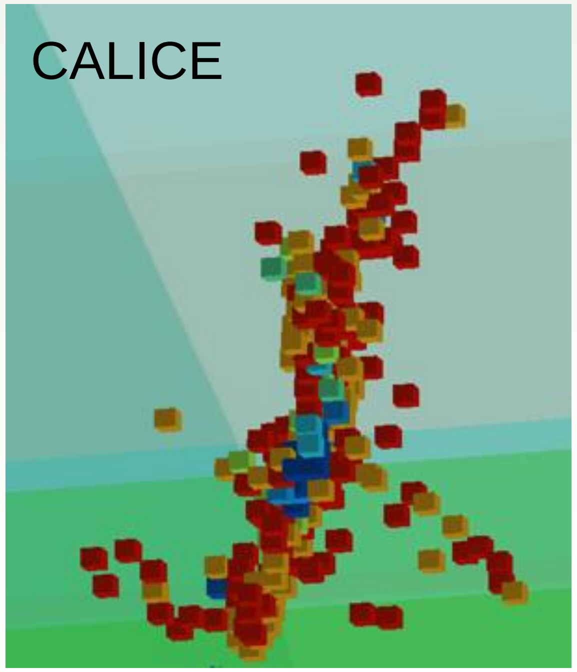


Image from https://news.voyage.auto/an-introduction-to-lidar-the-key-self-driving-car-sensor-a

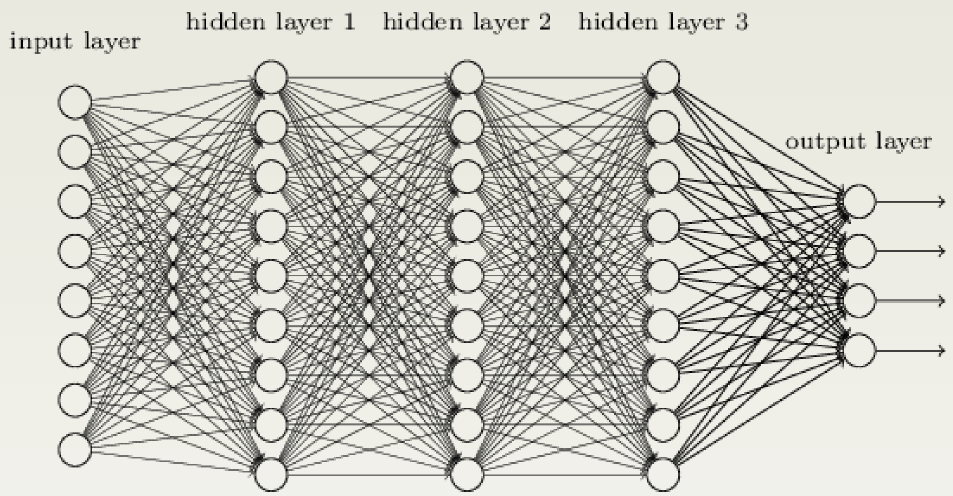


- Dense energy deposits
- Deposits connected by tracks

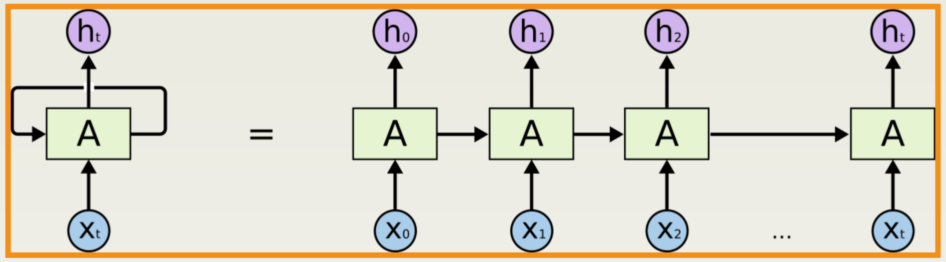
➞Showers have physical graph like structure
➞Hits can be represented by point clouds

Irregular Structures

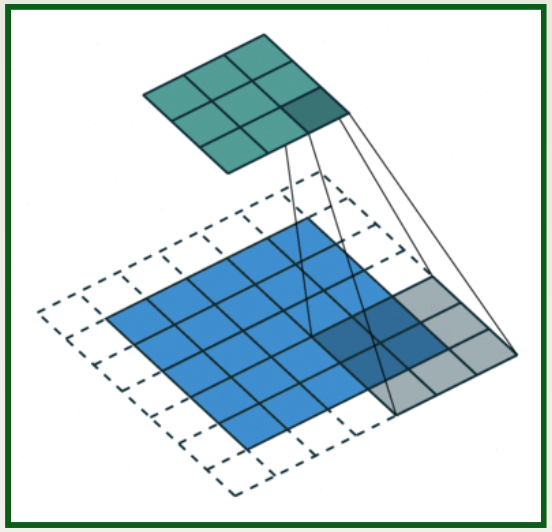
- Off-the shelf architectures…



Low input dimensionality



Clear sense of sorting / sequences



Regular grid

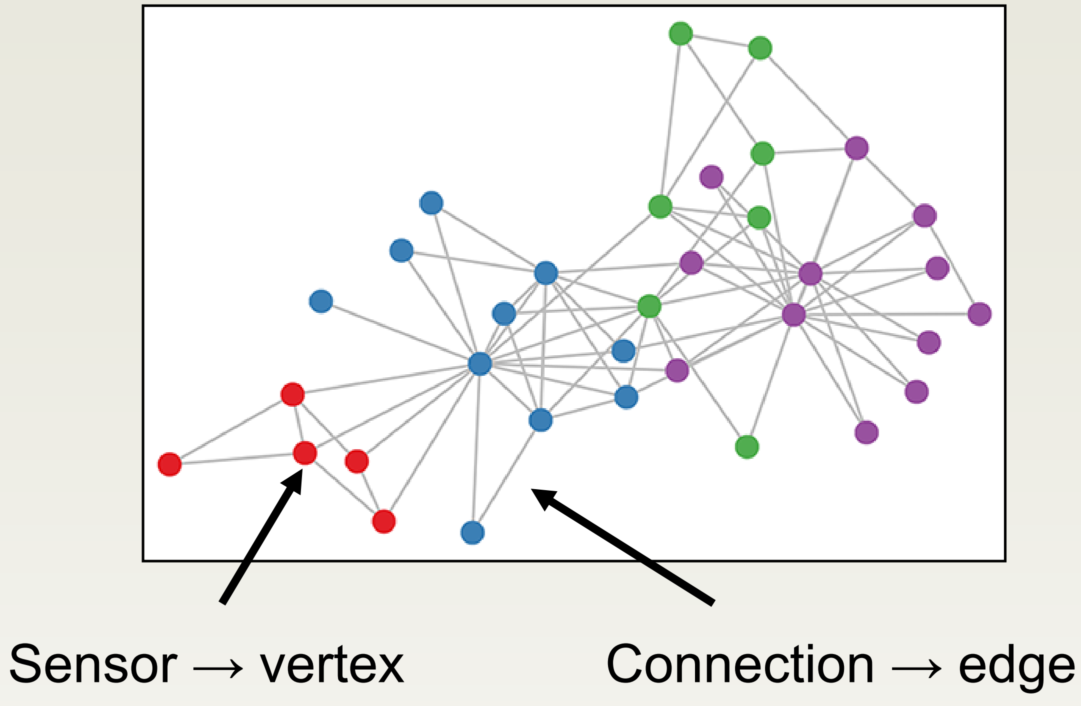
- ..do not represent particles or most sensor arrays in a detector
- Graph networks
  - No sorting required
  - No grid
  - Sense of connection
  - Basic principle: information exchange through edges (connections)
  - Very active area of research in CS

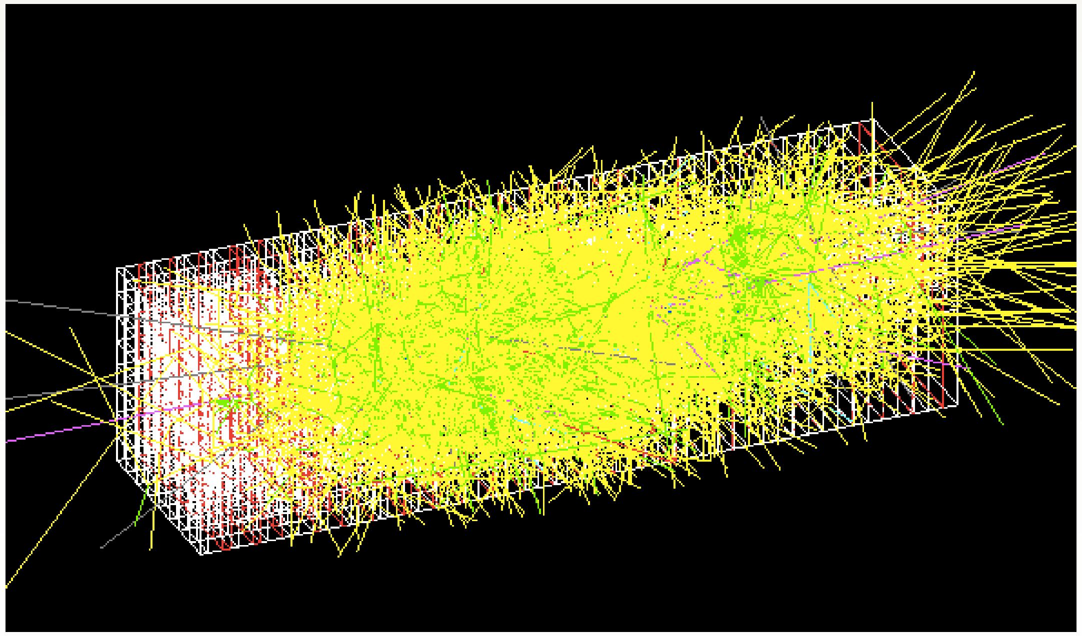
Brandes et al., 2008

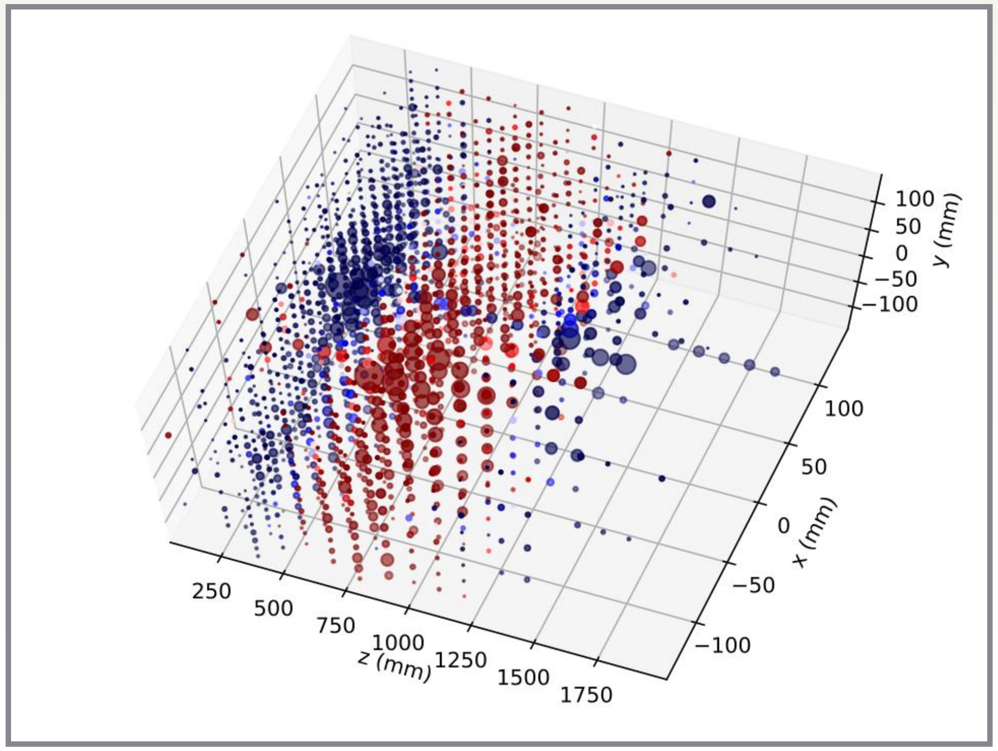
Going beyond CNNs

- Using graph neural networks for reconstruction
  - Represent showers as point clouds
  - In particularly interesting:
    dynamic graph networks learning space transformations (no human engineered edges)

- Here in a simplified irregular calorimeter
  - PbW, 35 cm x 35 cm x 2.2 m
- Predict fractions per hit for 2 overlapping charged pion showers
  - Energy: 10-100 GeV

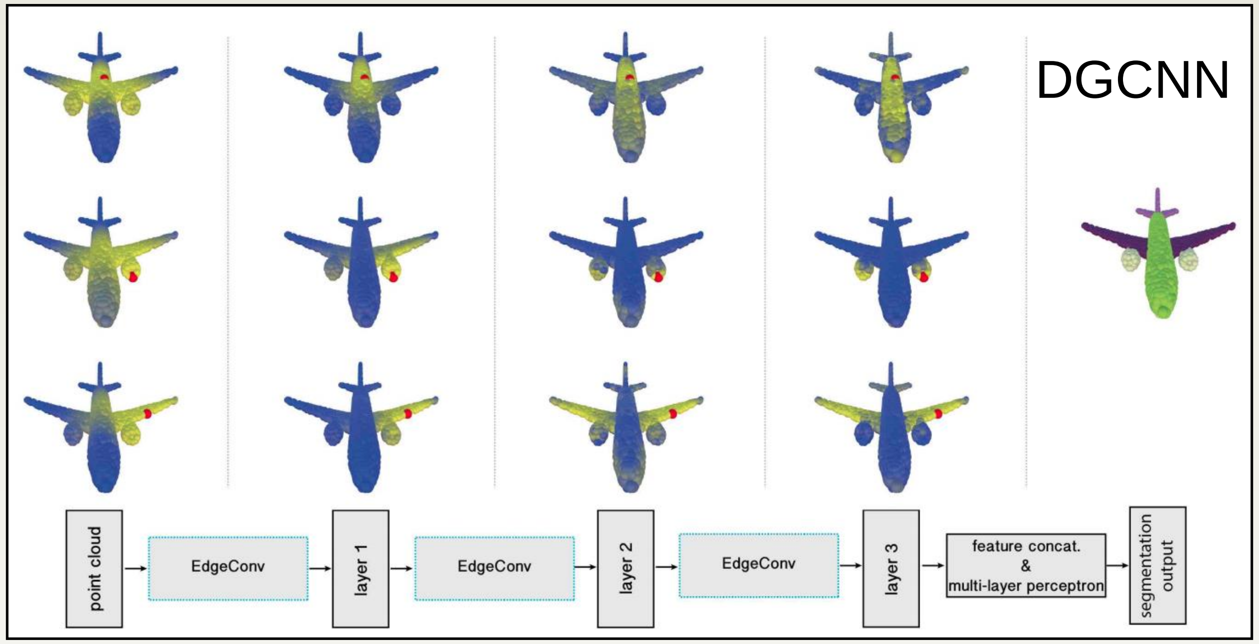






Applicable dynamic graph networks

- Proposal for 3D segmentation of point clouds: EdgeConv/DGCNN [1] similar to our problem
  - Transform features per vertex (sensor) (64)
  - Calculate distances in new feature space
  - Collect K neighbours
  - *Transform edge features*
    (distance vectors between sensors)
  - Collect maxima to determine new vertex properties



- Proven very powerful for segmentation
- Also successfully used for jet identification [2]

- Fractional assignment is not ‘just' segmentation

- Very resource demanding network architecture

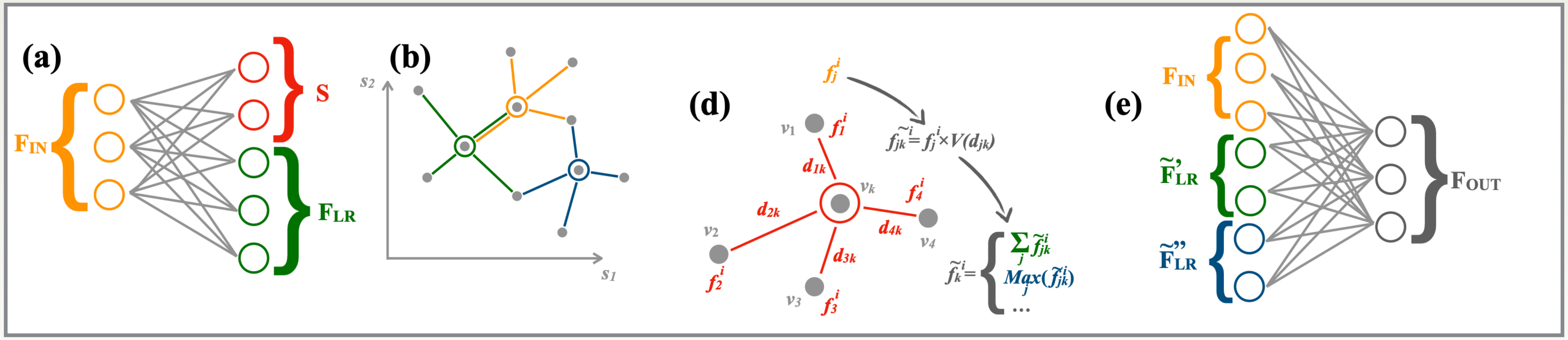
- Can we do better?

[1] Y. Wang, et al, arXiv:1801.07829
[2] H. Qu, L. Gouskos, arXiv:1902.08570

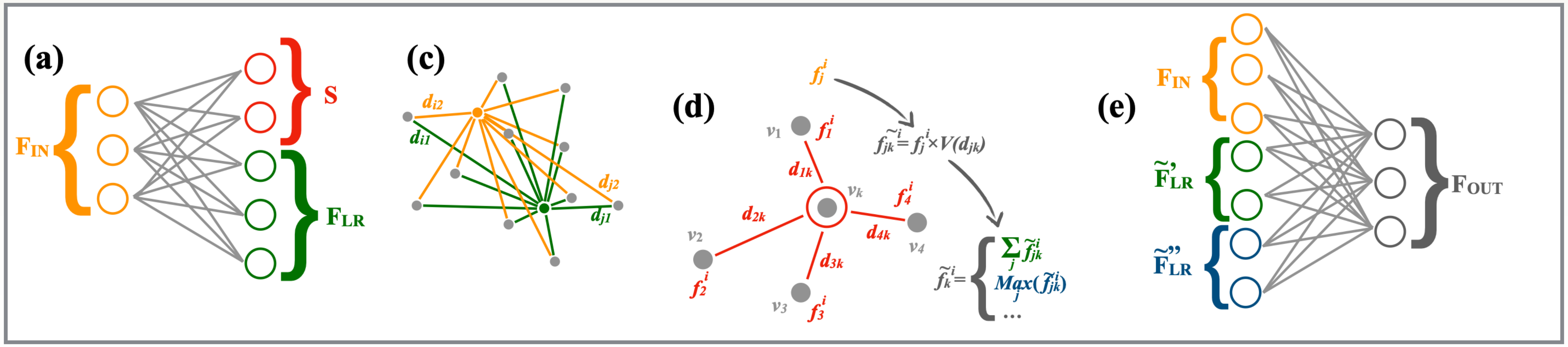
GravNet/GarNet

- Most resource demanding operation in DGCNN
  - Determine neighbours in F_{IN} dimensions
  - Iteration over edges between K neighbours in F_{IN} dimensions
- GravNet/GarNet circumvent this problem
  - Split coordinate and feature space

- GravNet

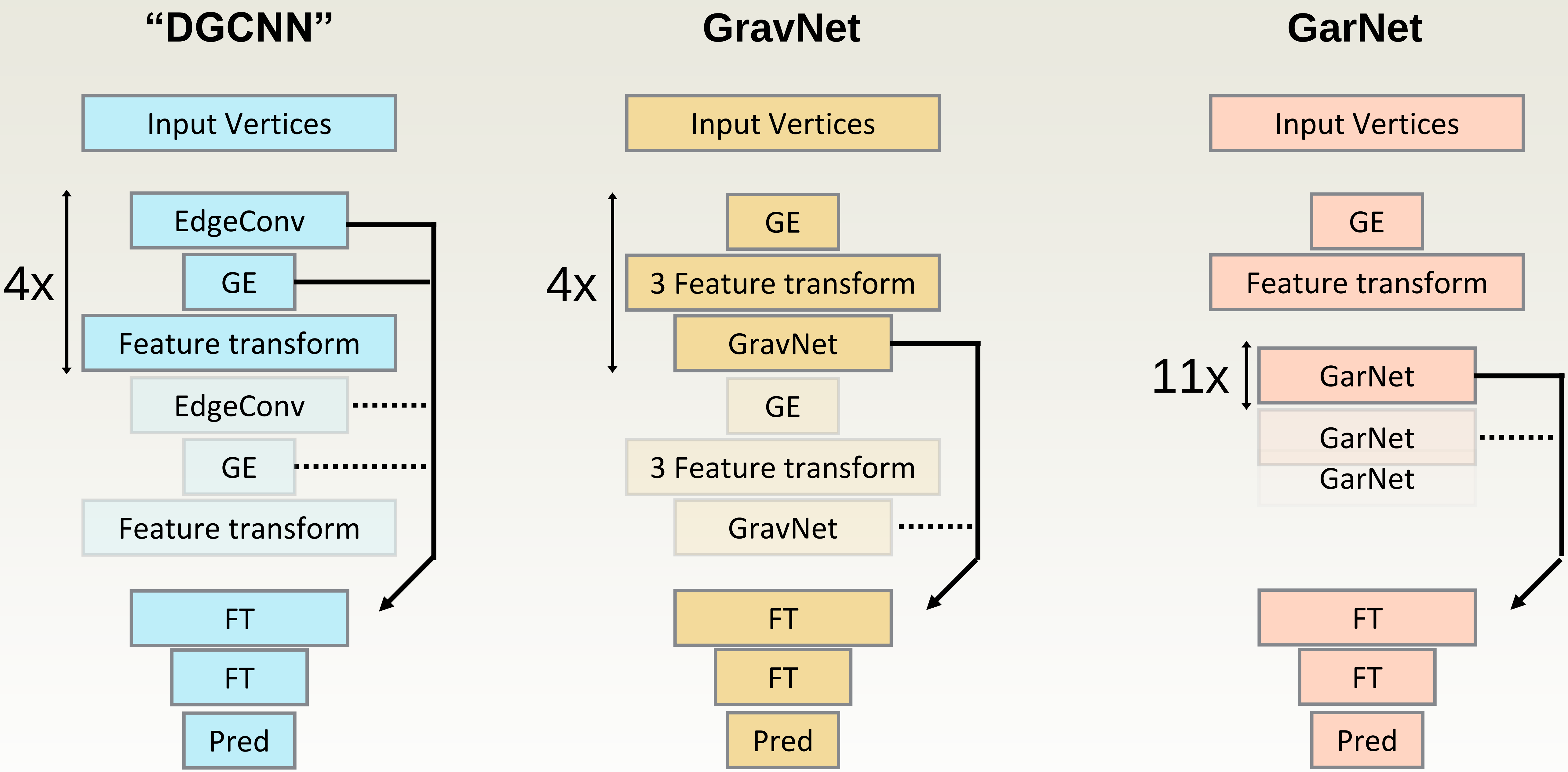


- GarNet



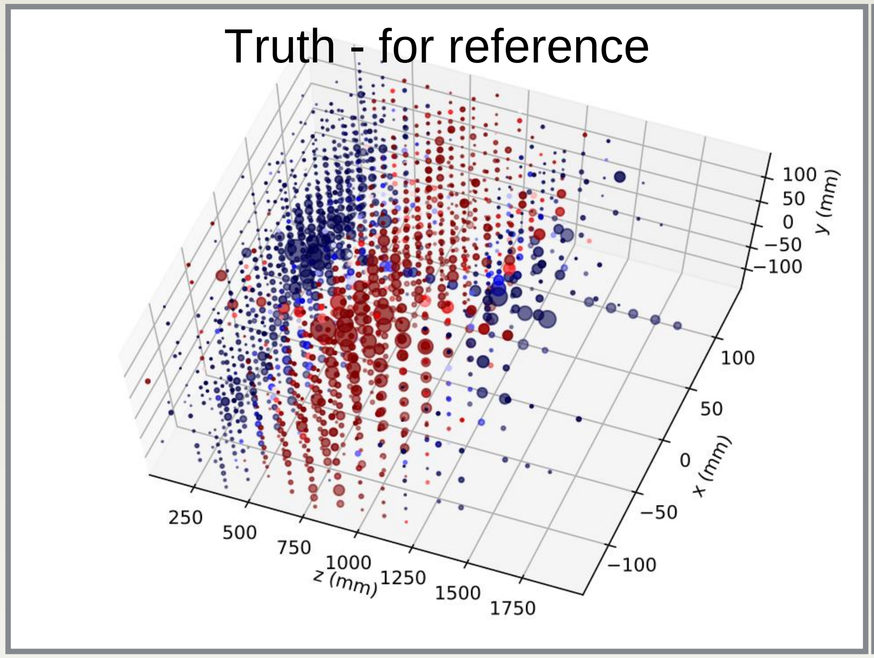
S.R. Qasim, J.K, Y. Iiyama, M Pierini arXiv:1902.07987, EPJC

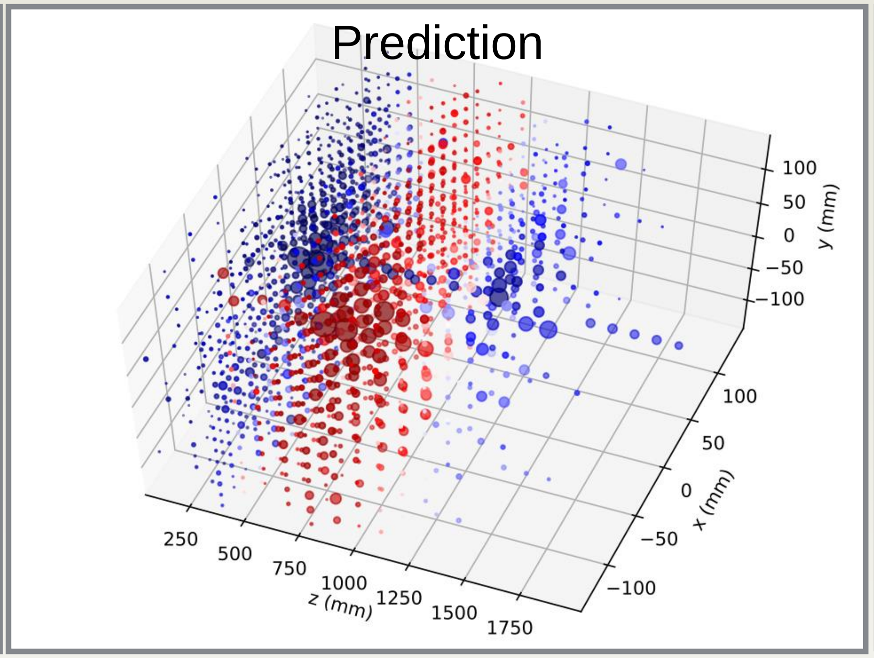
Models

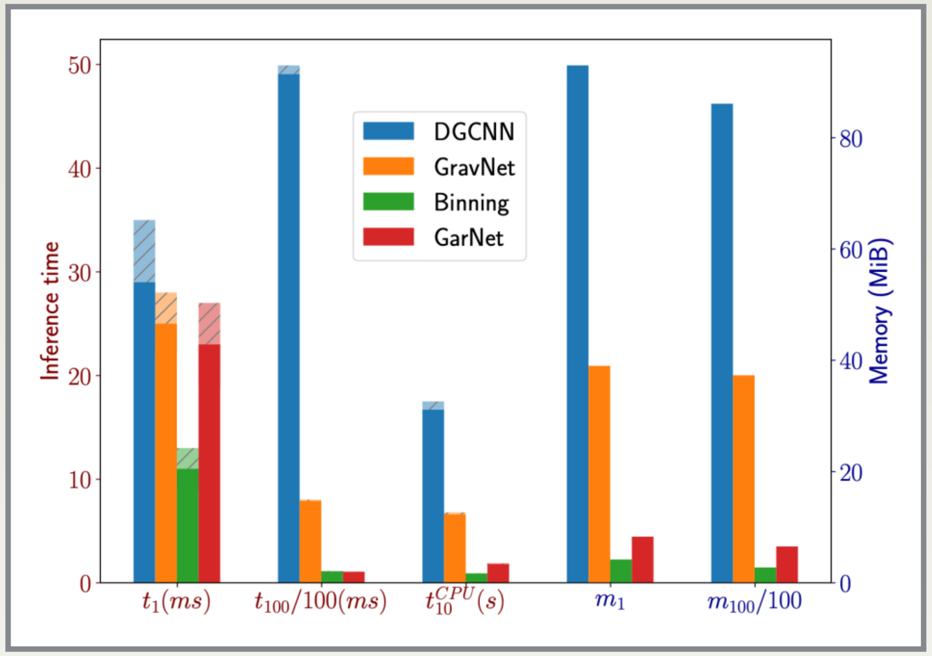


- Similar total depth (counting all trainable transformations)
- All models approx 100k free parameters

Results





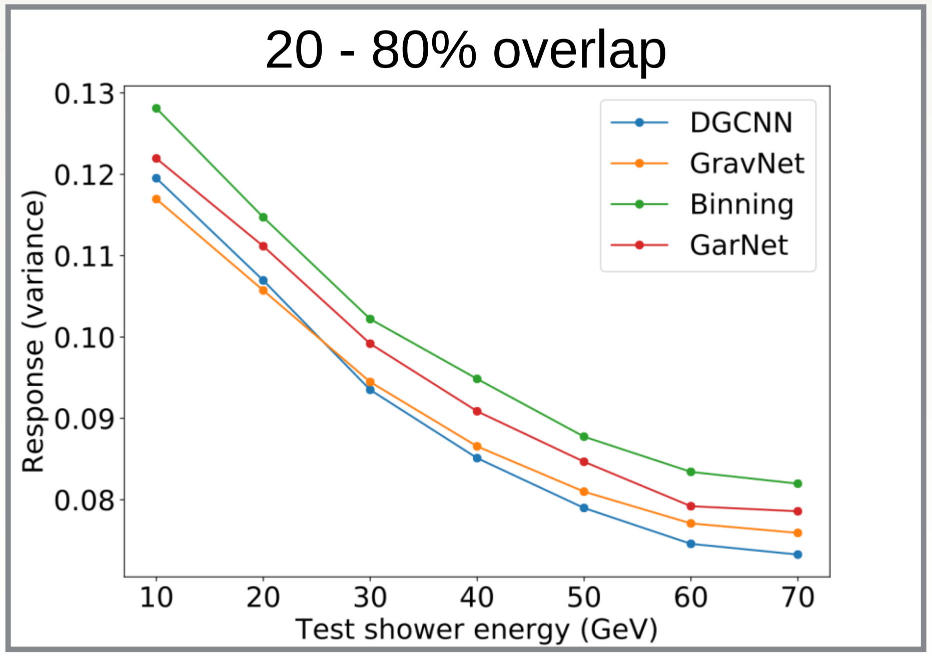


$$L = \sum_k \frac{\sum_i \sqrt{E_i t_{ki}} (p_{ki} - t_{ki})^2}{\sum_i \sqrt{E_i t_{ki}}},$$

$$R_k = \frac{\sum_i E_i p_{ik}}{\sum_i E_i t_{ik}}$$

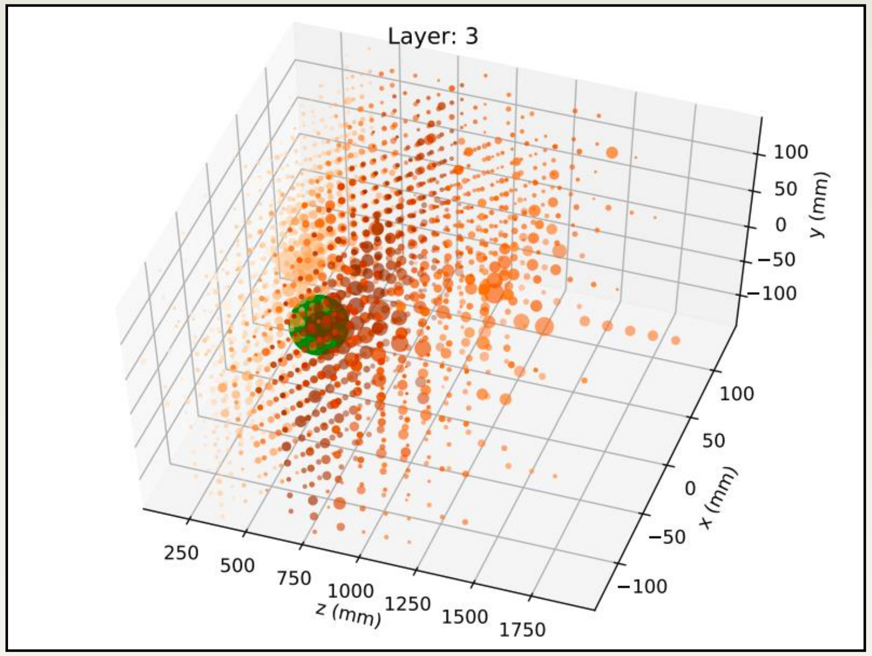
- The graph network architectures outperform the CNN approach
- Similar performance but lower resource requirements of GravNet versus DGCNN
- Competitive performance and very low resource requirements for Garnet

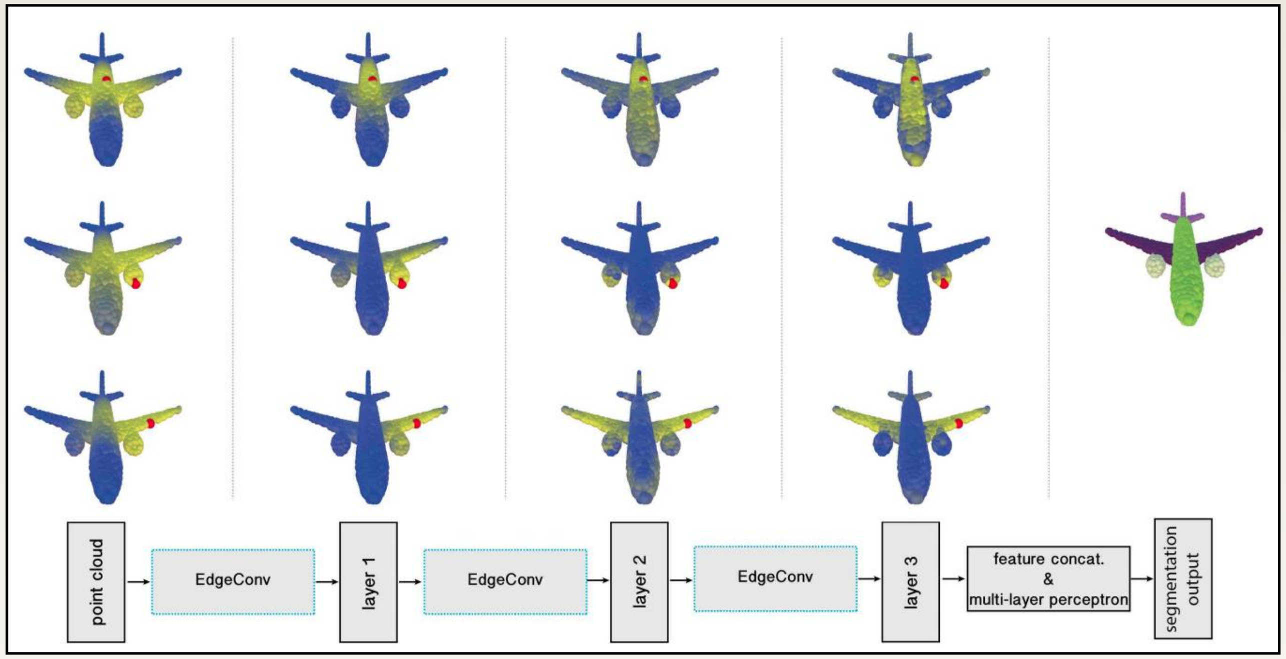
- These architectures are applicable to (sparse) data with any structure, e.g. tracking, jets, …

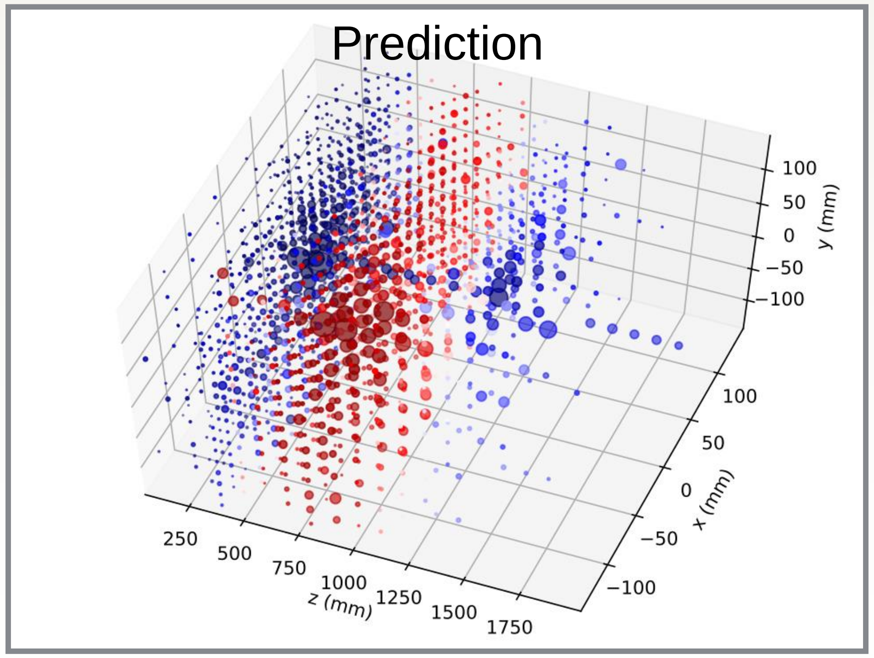


S.R. Qasim, J. K, Y. Iiyama, M Pierini arXiv:1902.07987, EPJC

- Visualise distances in the latent coordinate space



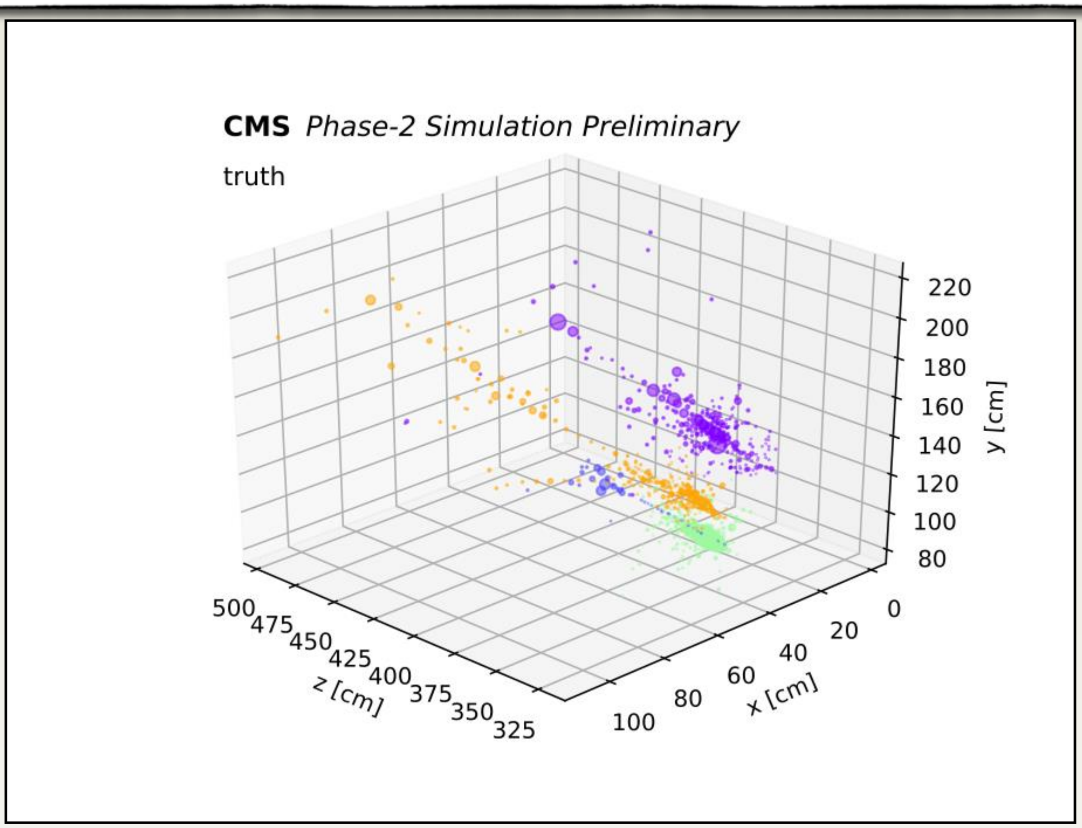


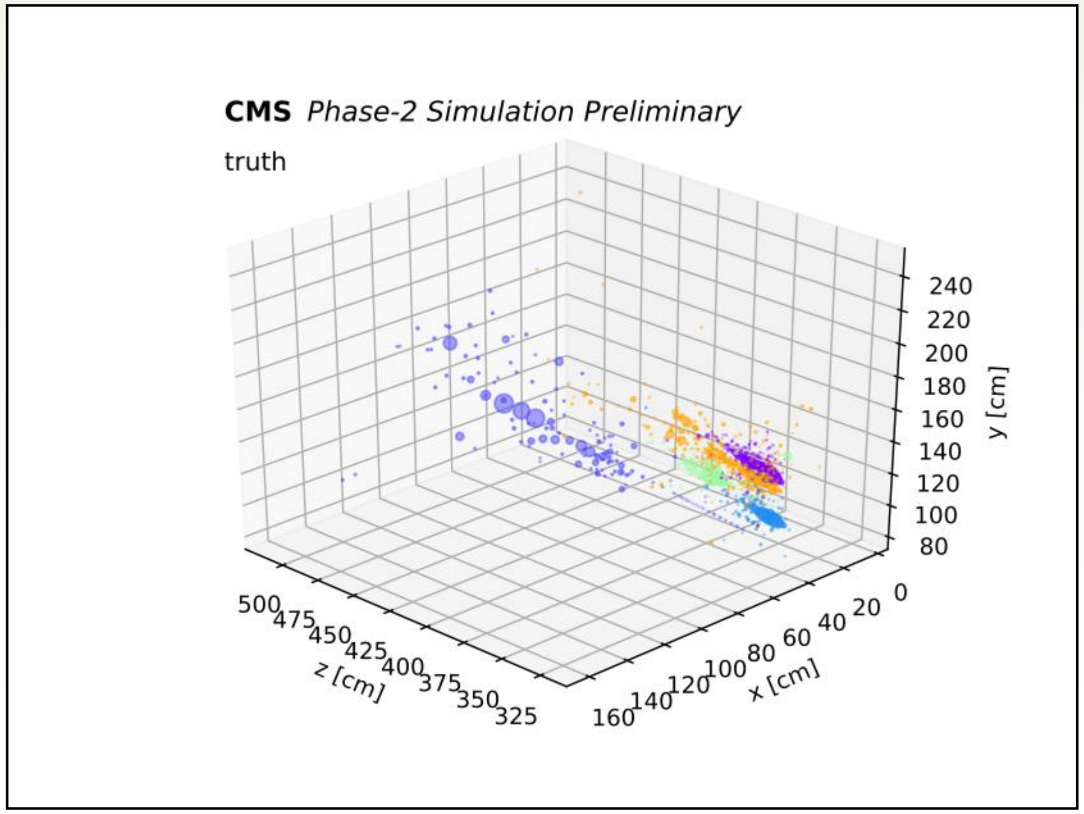


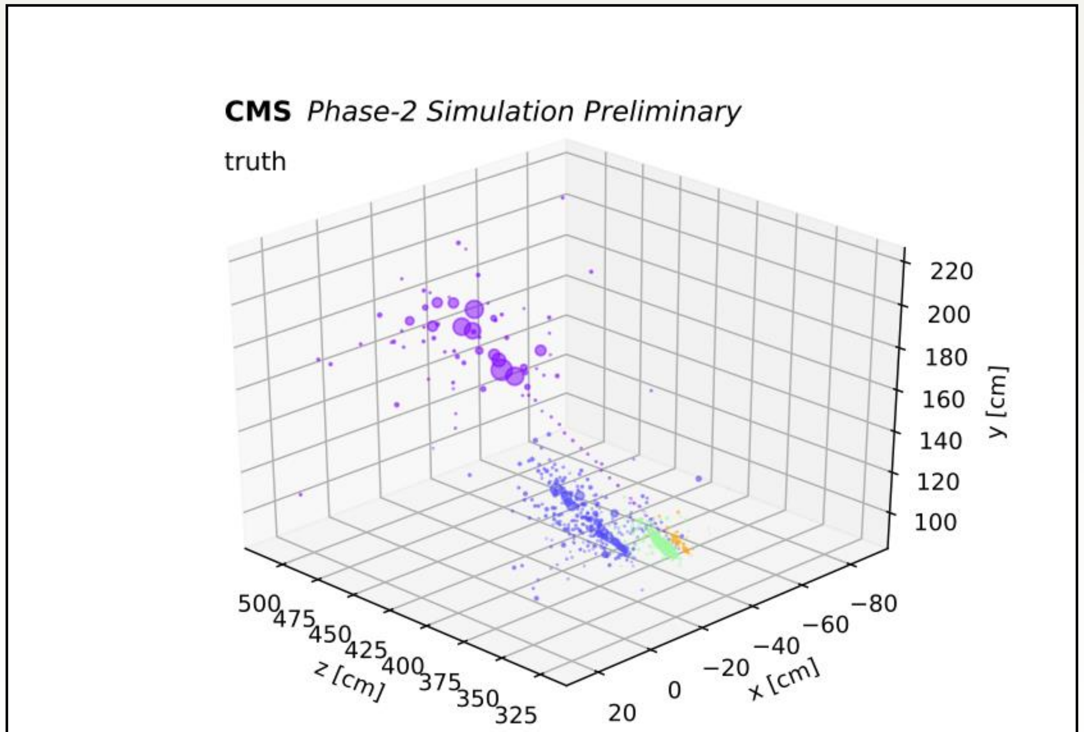
- *Without direct supervision, the networks tend to cluster vertices belonging to the same shower*
- Seems to be a common feature of distance based dynamic graph networks

Application to CMS HGCal

- Dataset
  - Full CMS HGCal simulation
  - 1-5 showers from electrons, photons, muons, charged pions within DR=0.5
  - 10-100 GeV
  - About 500k events
  - Hits pre-clustered on each layer (less inputs)
- Use GravNet with small adjustments
  - 5 output nodes, predicting shower fractions
  - 2 additional message passing layers in latent space

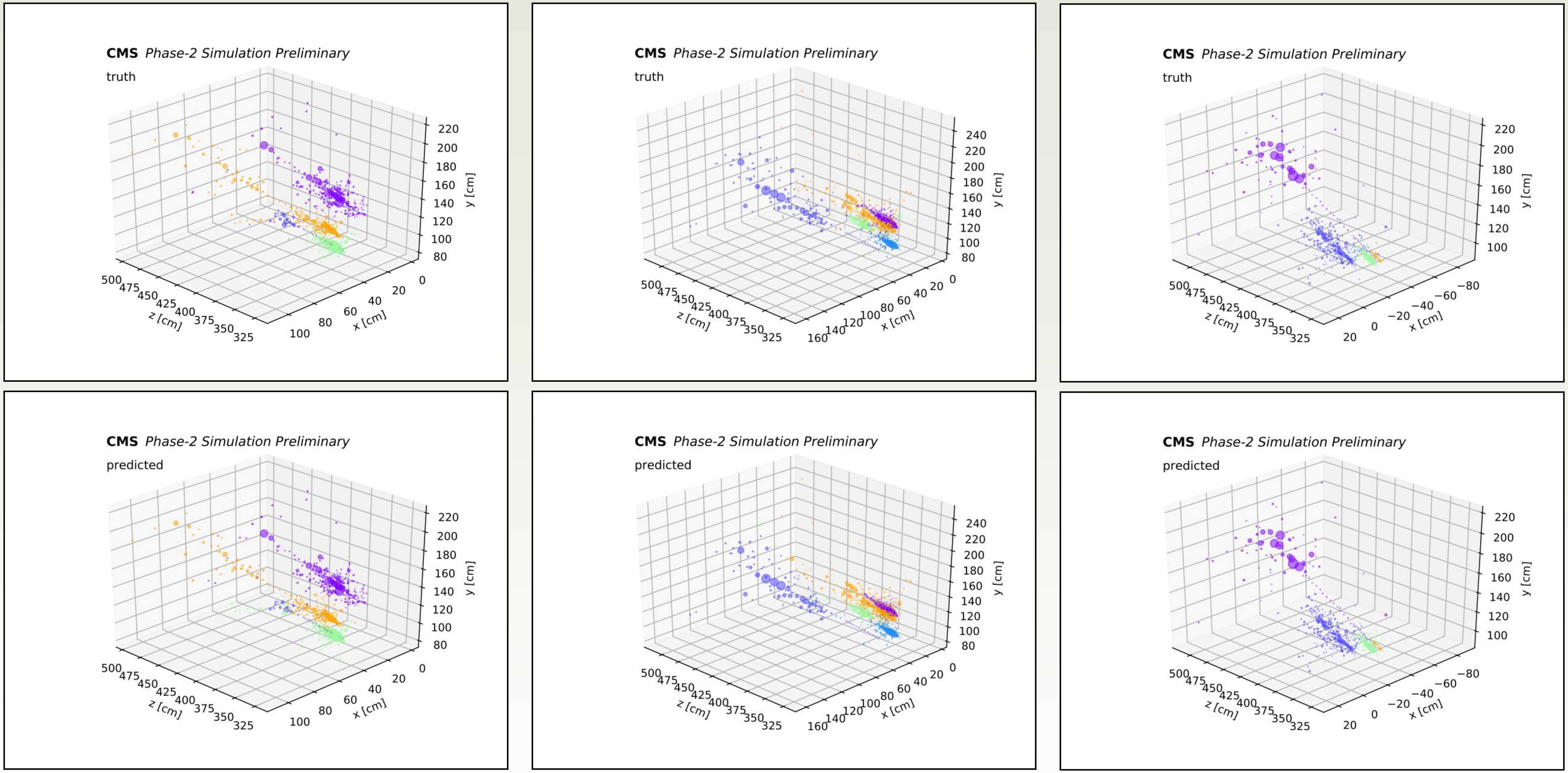






CMS DP-2020/001

Results

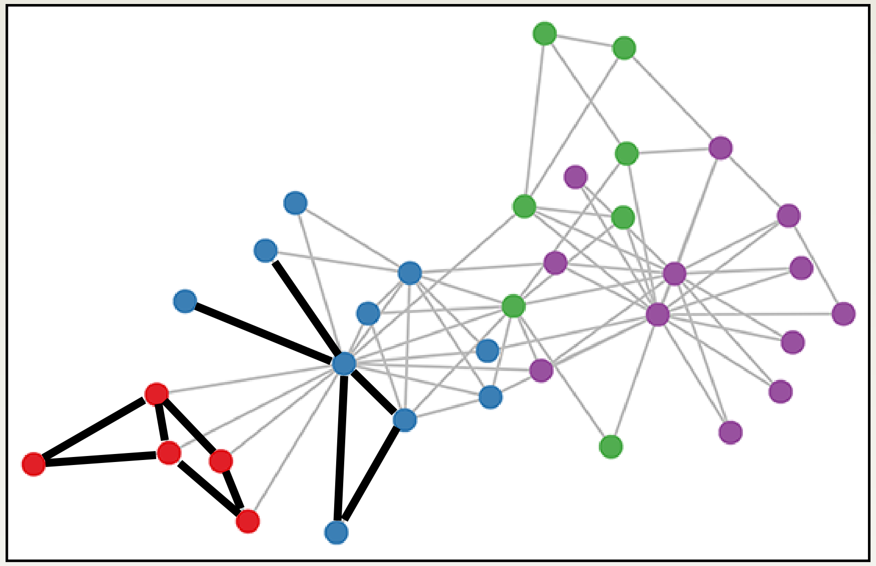


- *Excellent shower reconstruction*
- But what if there are more than 5 particles?

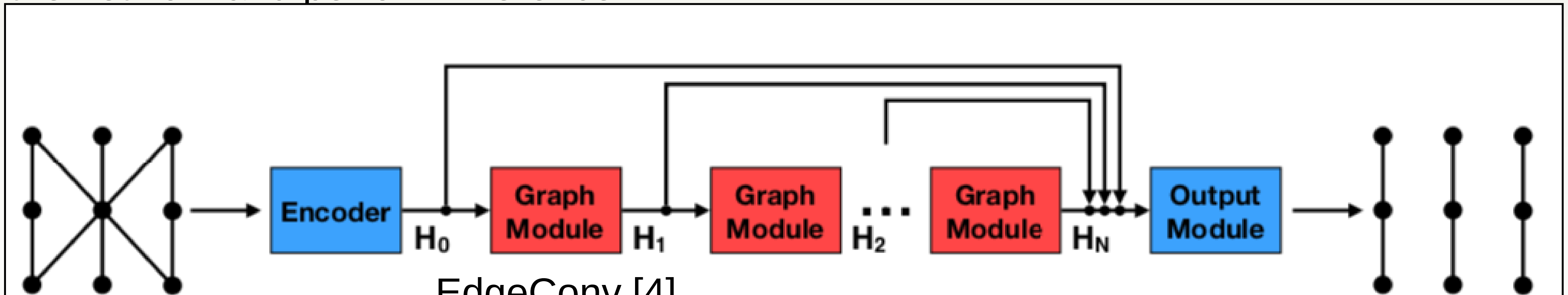
CMS DP-2020/001

One approach: Edge classifiers

- Inspired by HEP.TrkX [1,2], edge classifiers can overcome the problem
- Objects appear as vertices that are connected to each other, but not connected to others



- Edges can carry additional information like particle ID
- Recipe [3]:
  - Pre-define a graph containing all possibly true edges (e.g. neighbours within a sphere)
  - Train the network and perform inference



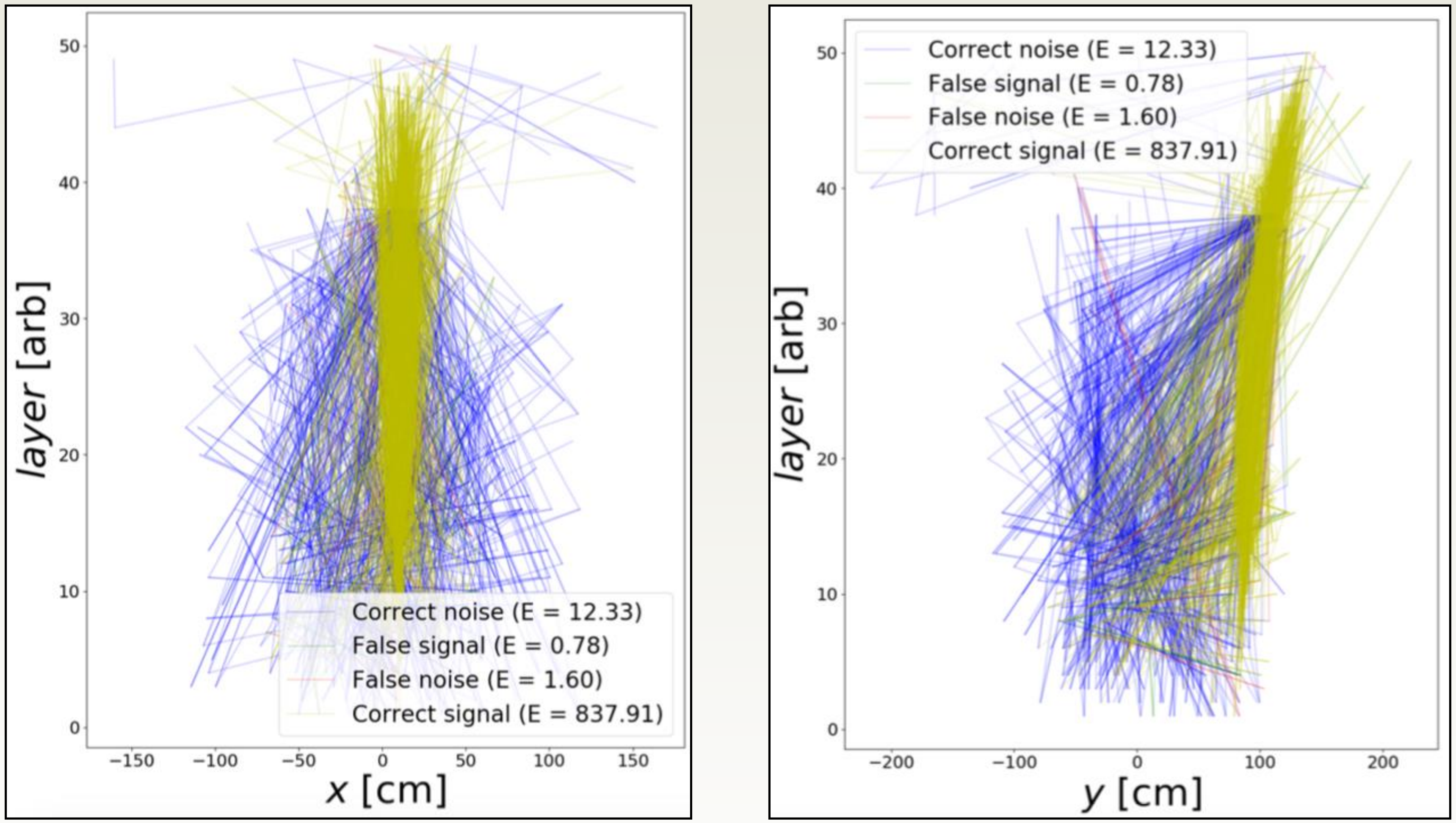
EdgeConv [4]

  - Select edges with a predicted probability of more than 0.5 to be true as connections

[1] S. Farrel et al, arxiv:1810.06111,
[2] 10.1051/epjconf/201715000003
[3] X. Ju et al, https://ml4physicalsciences.github.io/files/NeurIPS_ML4PS_2019_83.pdf
[4] Y. Wang, et al, arXiv:1801.07829. (DGCNN)

Edge Classifier in calorimeter

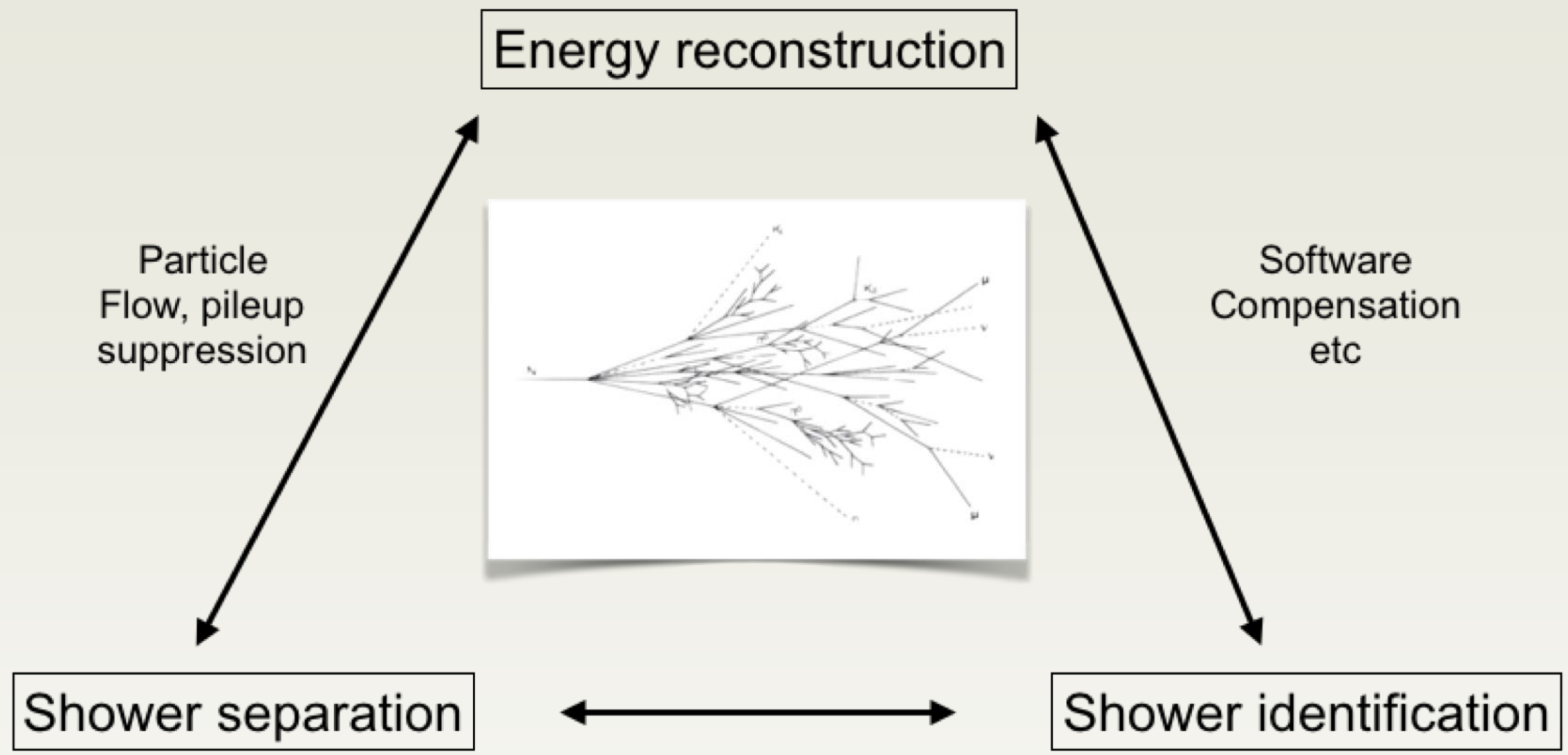
- CMS HGCal
- Single charged pions in 0 PU



- Excellent discrimination between noise and signal
- Needs more developments for fractional assignments, very small objects
- N x K edges need to be evaluated to determine object and its properties
  - Mean over edges for properties or e.g. weight with edge score

X. Ju et al, https://ml4physicalsciences.github.io/files/NeurIPS_ML4PS_2019_83.pdf

Take a step back



- What we actually want: particle ID, momentum, position
- Segmentation just a tool
- Standard chain has many redundancies
  - Seeding (pattern recognition)
  - Clustering (pattern recognition)
  - Software compensation (pattern recognition)
  - ID (pattern recognition)
  - PFlow (pattern recognition)
- Always the same patterns
- One-stage approach can save resources and is easier to maintain

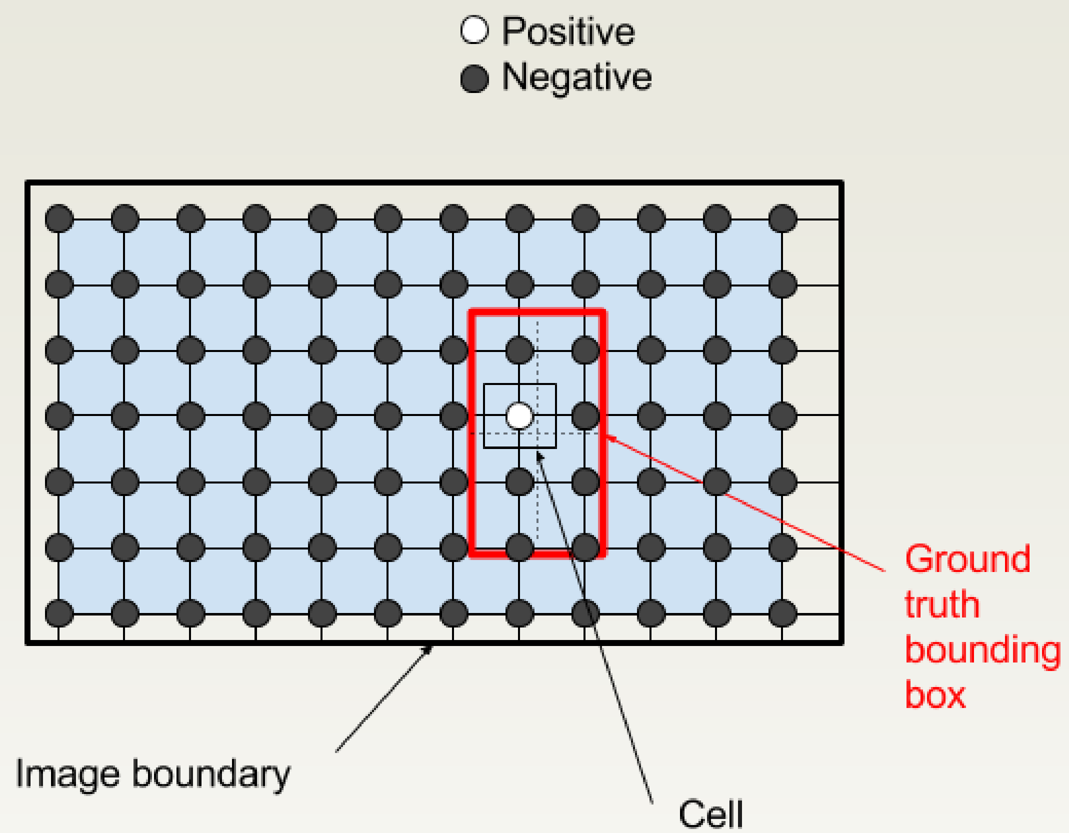
A look at computer vision


T. Lin et al, arXiv:1405.0312

- Well known from object detection in images
- Two main approaches:
  - "Traditional' anchor point based approaches [1-4], …
  - Anchor-free approaches, using each pixel [5,6, …]

[1] J. Redmond et al, arXiv:1506.02640
[2] Y. Hu et al, arXiv:1803.11187
[3] R. Girshick, arXiv:1504.08083
[4] T. Lin et al, arXiv:1708.02002
[5] N. Wang et al, arXiv:1904.01355
[6] X. Zhou et al, arXiv:1904.07850

Anchor point based methods



- Anchor points (M x M per image)
- Assign object score/bounding box to anchor point
- Object can be found multiple times

- Anchor points grow with with N^(dim), make implicit assumptions on object size

- *Not suitable for reconstruction based on high-dimensional detector signals*

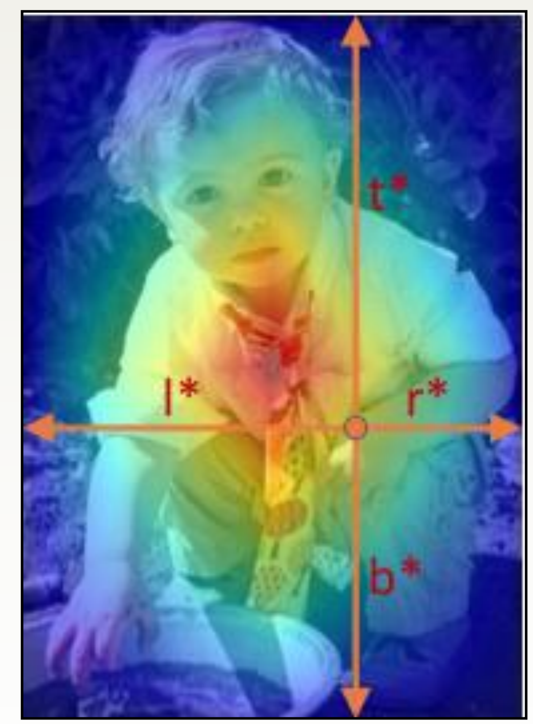
Figures: towardsdatascience.com

Key point methods

- Identify key points of the object
- Predict object properties from key points

Problem: identify the key points

- Also predict ‘center-score’
- Select highest score in the area as key point
  - ***Seed identification!***
  - Heavily relies on objects to have a center: problematic for a particle

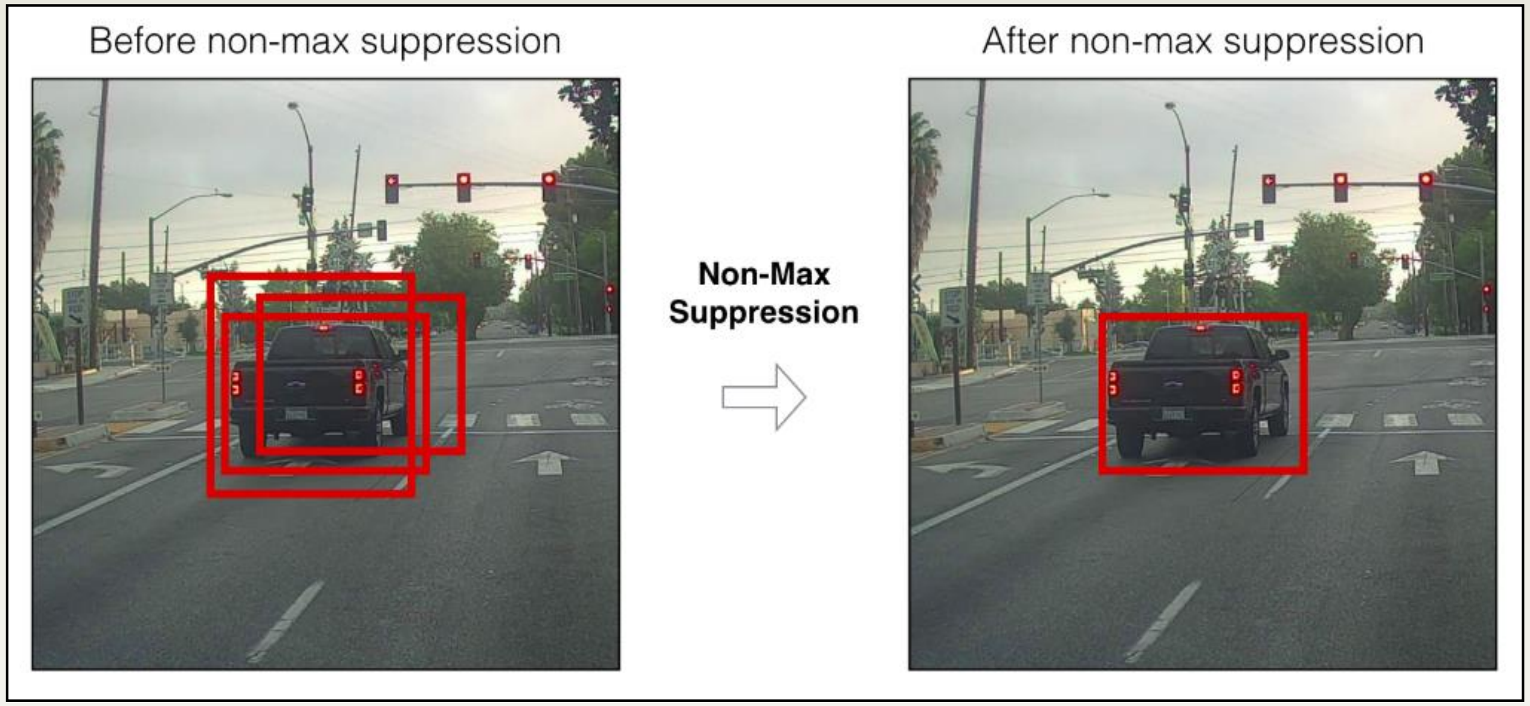


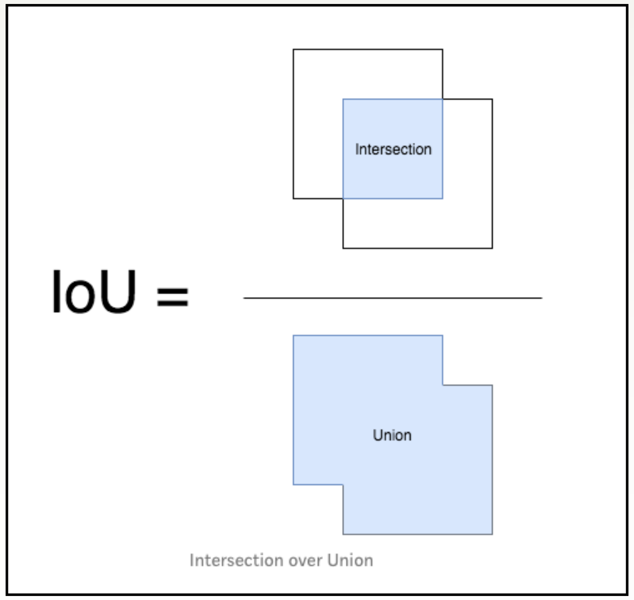
- Remaining ambiguities still need to be resolved

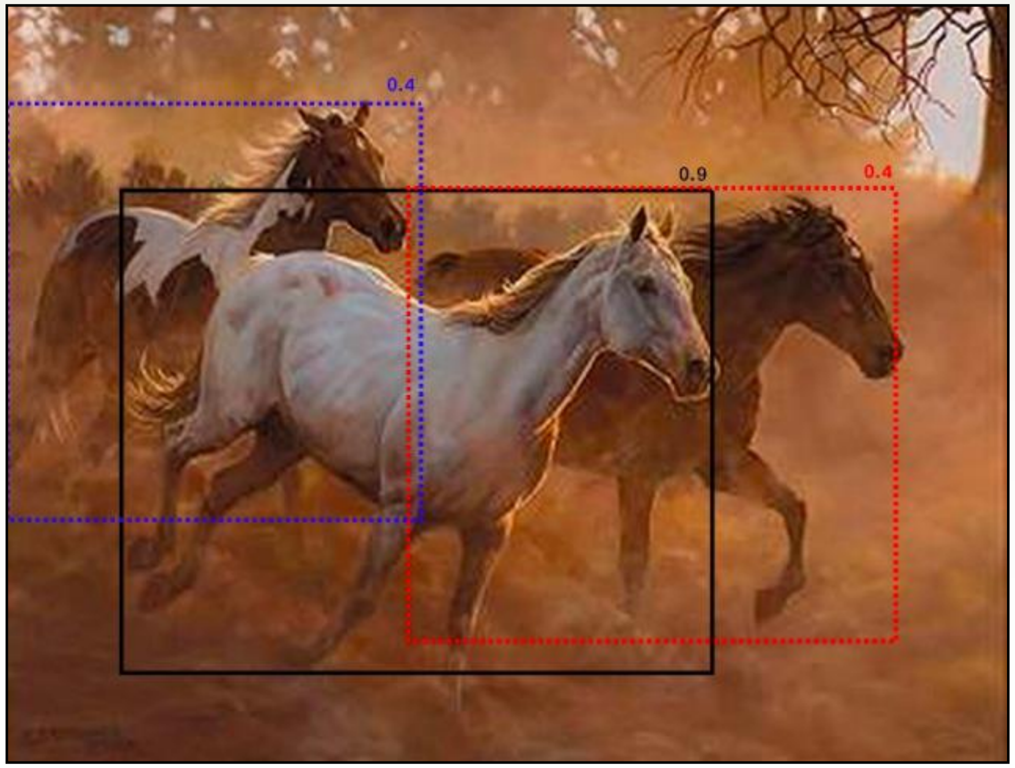
N. Wang et al, arXiv:1904.01355
X. Zhou et al, arXiv:1904.07850

Non maximum suppression

- Start with highest score
- Downweight ‘close’ by objects using IoU (Soft NMS)
- Relies on bounding boxes
- *Not easily adaptable to particles in detectors*







N. Bodla et al, arXiv:1704.04503
Figures: towardsdatascience.com

Segmentation and Clustering

- Maximum number of objects per image/point cloud: number of pixels/vertices

- Learn to move pixels towards the object center
- Map to Gaussian probability

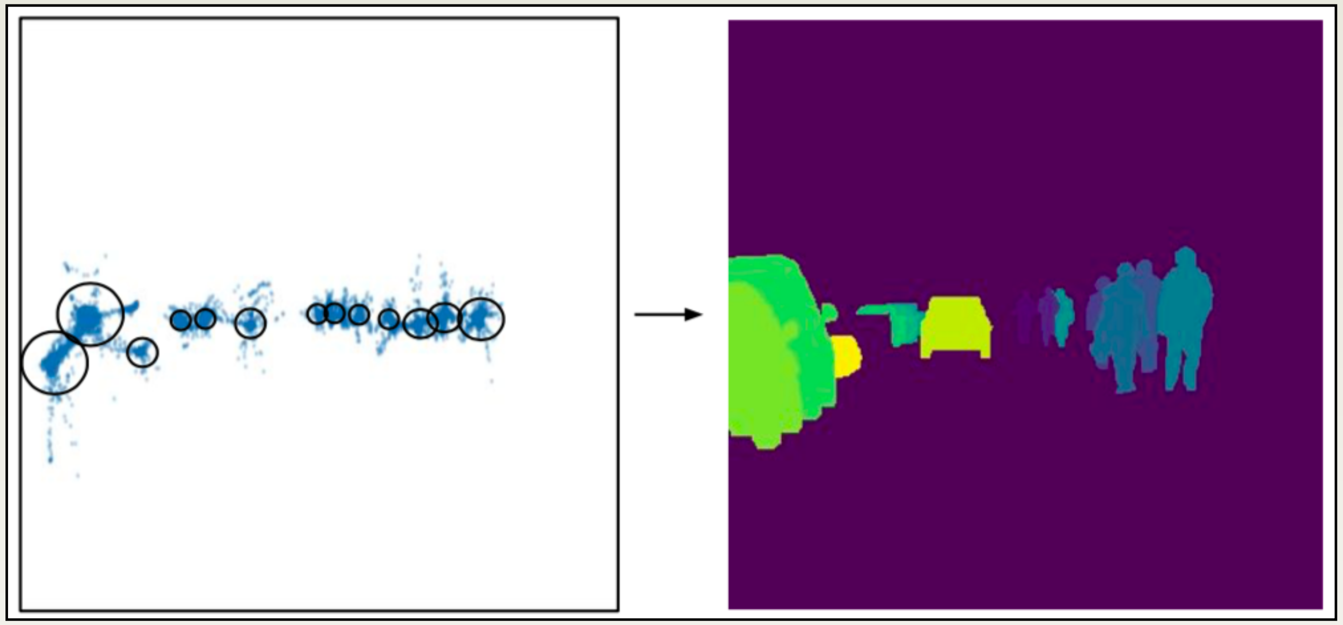
$$\phi_k(e_i) = \exp\left(-\frac{\|e_i - C_k\|^2}{2\sigma_k^2}\right)$$

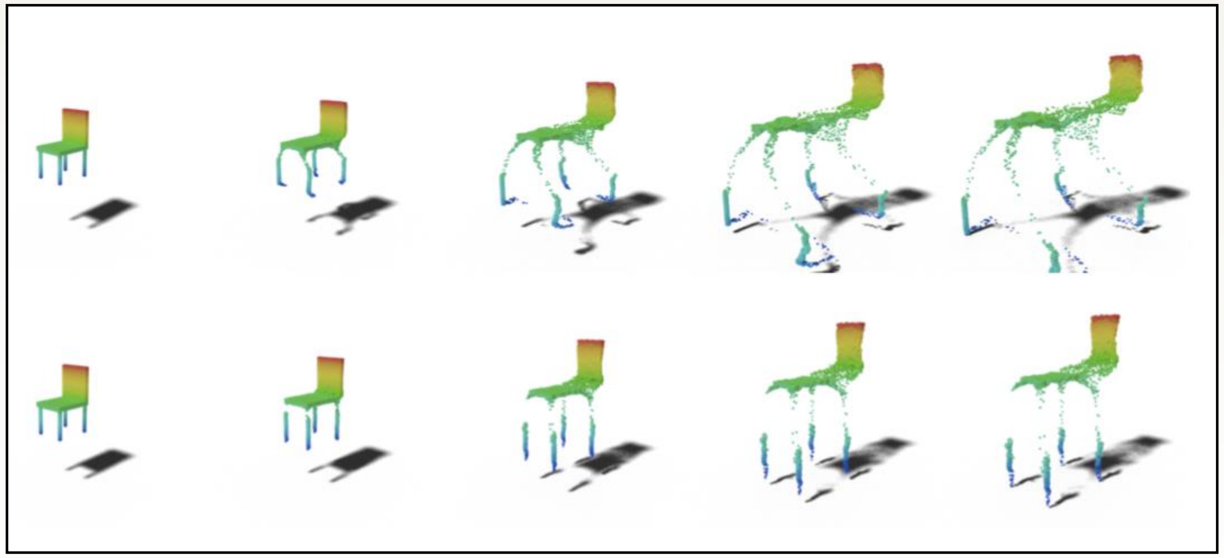
- Assign seed score

$$\mathcal{L}_{\text{seed}} = \frac{1}{\text{N}} \sum_i^{\text{N}} \mathbb{1}_{\{s_i \in S_k\}} \|s_i - \phi_k(e_i)\|^2 + \mathbb{1}_{\{s_i \in \text{bg}\}} \|s_i - 0\|^2$$

- Collect (from highest seeds score) around the seeds

- *'Only' performs segmentation*
- *Heavily relies on the center of an object*
  - *Problematic concept for particles*

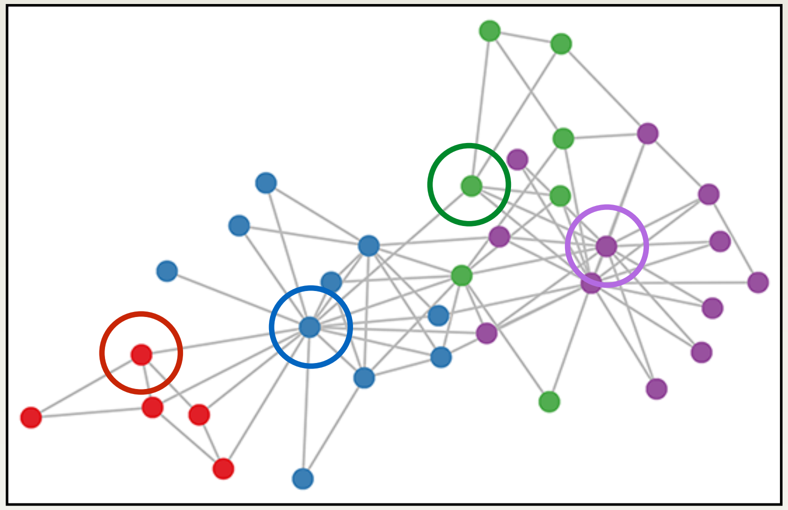




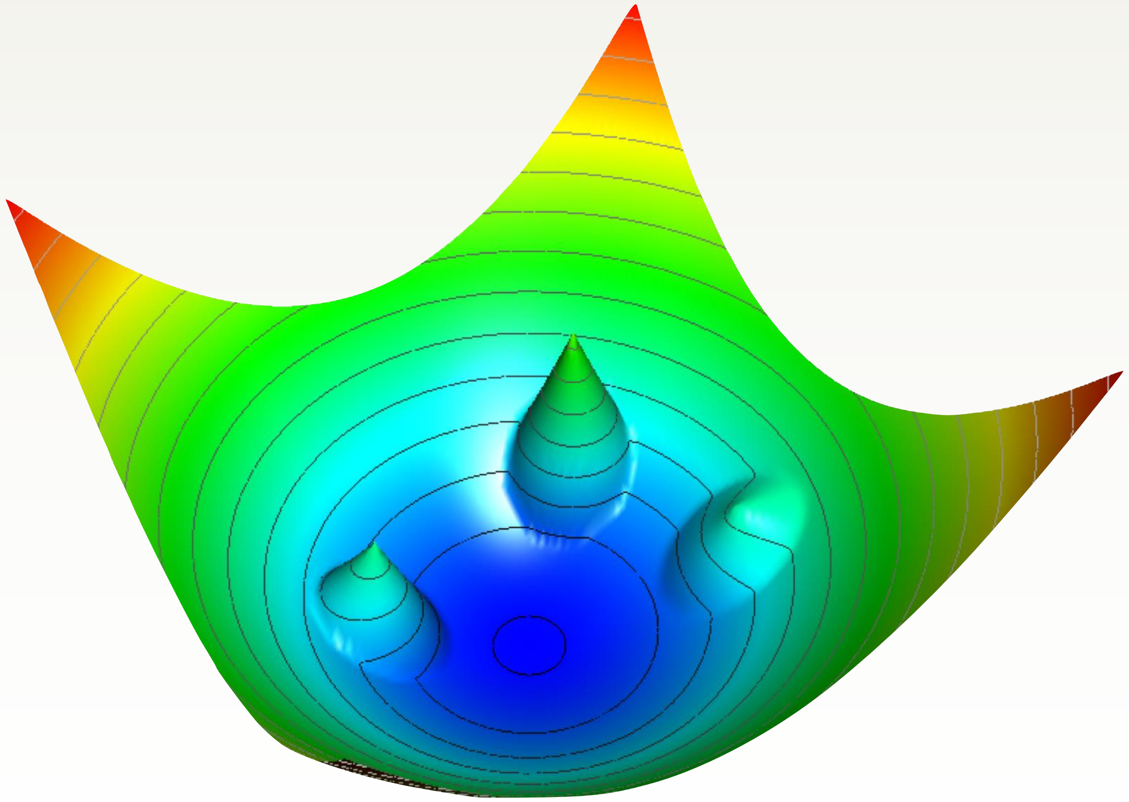
D. Neven et al, arXiv:1906.11109
B. Zhang, P. Wonka, arXiv:1912.00145

Object condensation

- Aim
  - Determine object properties (e.g. particle 4 momenta, ID) (graphs, images, …)
  - Aggregate all object properties in representative 'condensation point'
  - Detach input space (3D/4D/5D) from output space
  - Resolve ambiguities without IoU (boxes) concept
  - Allow for fractional/ambiguous assignments



- Define truth:
  - Assign each vertex to one object (e.g. highest fraction)
  - Assign all object properties to each assigned vertex



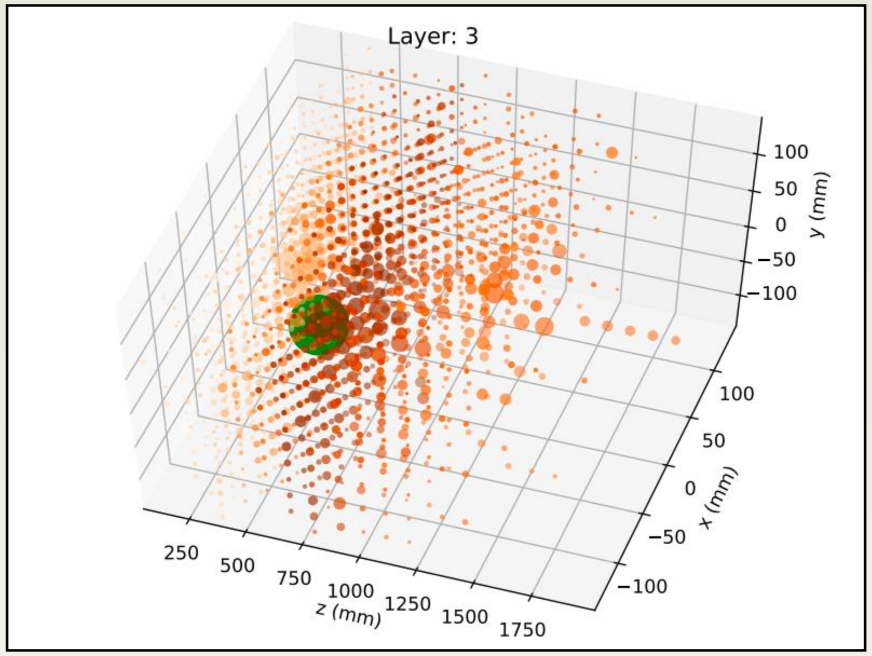
- Predict per vertex
  - Object properties
  - Confidence β
  - Cluster coordinates x
- Define charge, attractive and repulsive potential

Condensate and predict

$$\breve{V}_k(x) = ||x - x_\alpha||^2 q_{\alpha k}, \text{ and}$$

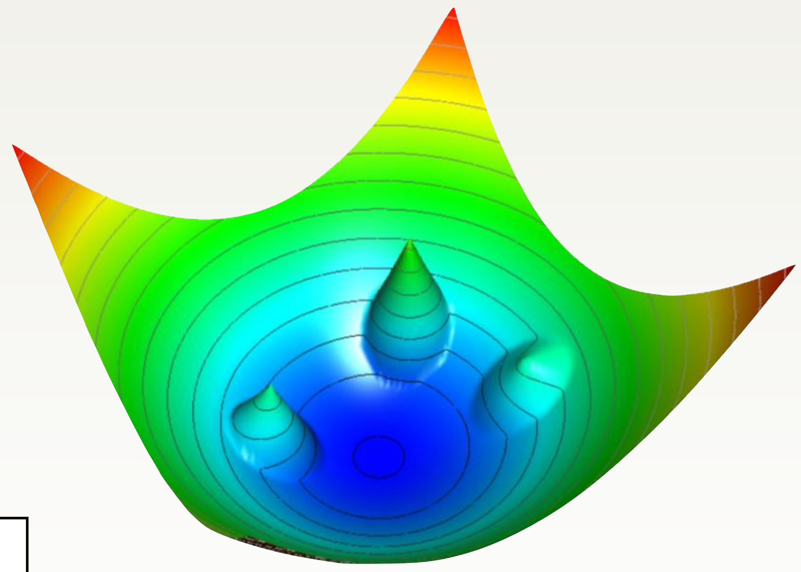
$$\hat{V}_k(x) = \max(0, 1 - ||x - x_\alpha||) q_{\alpha k}.$$

Maximum charge vertex for object k



- Maximum β/charge vertices *are* center points *
- Encourage network to select one representative point per object k

$$L_\beta = \frac{1}{K}\sum_k (1 - \beta_{\alpha k}) + s_B \frac{1}{N_B}\sum_i^N n_i \beta_i,$$



- Also weight object property loss with β

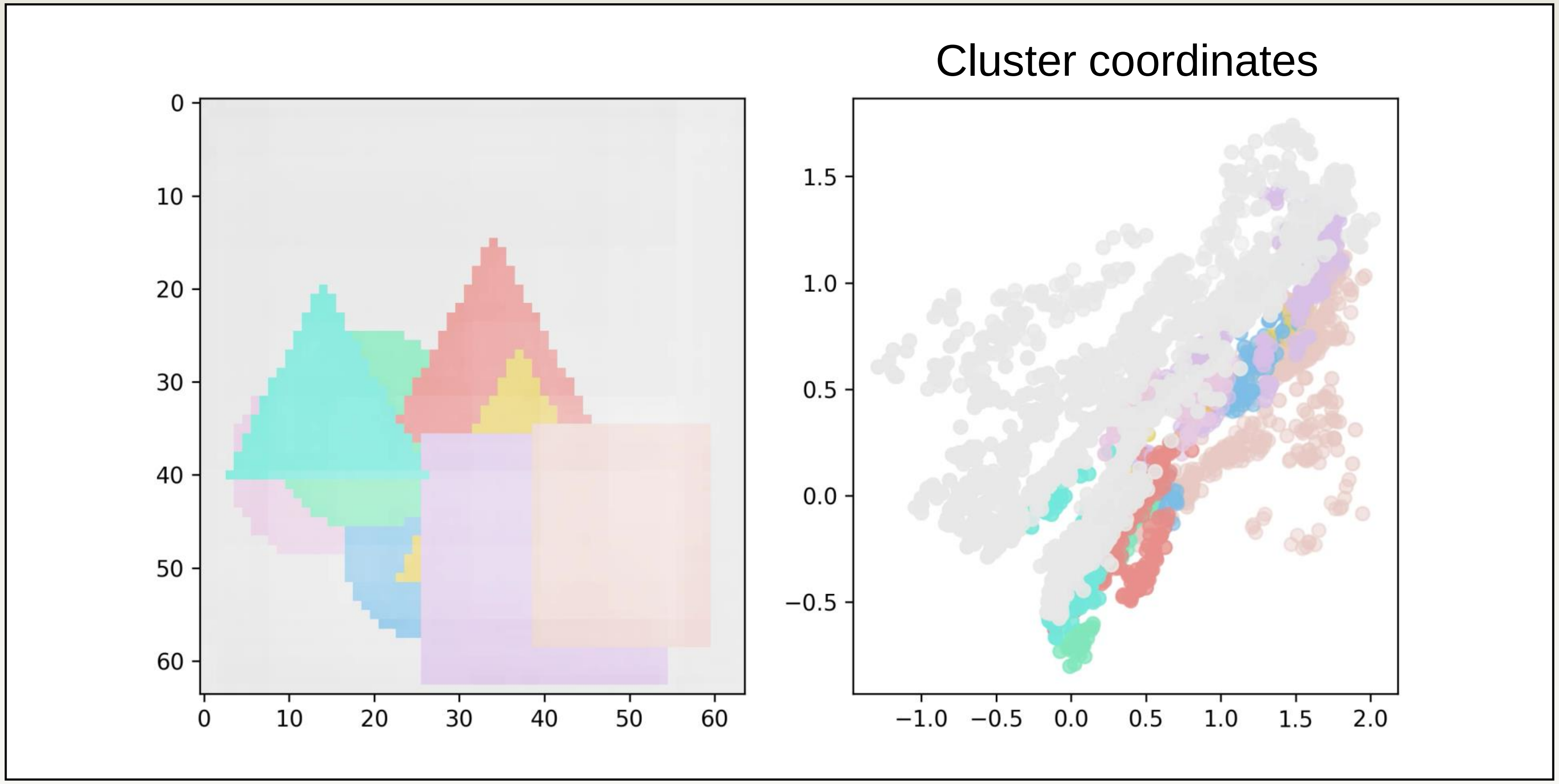
$$L_p = \frac{1}{\sum_{i=0}^N (1 - n_i)\,\mathrm{arctanh}^2\,\beta_i} \sum_{i=0}^N L(t_i, p_i)(1 - n_i)\,\mathrm{arctanh}^2\,\beta_i$$

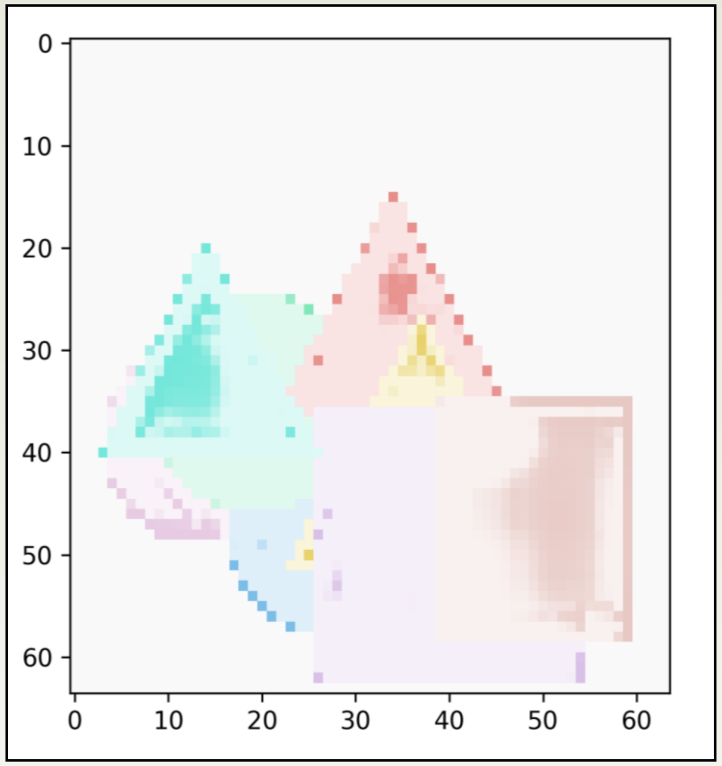
- *Condensation points will carry all object properties*
- *Very natural approach for dynamic graph NN*

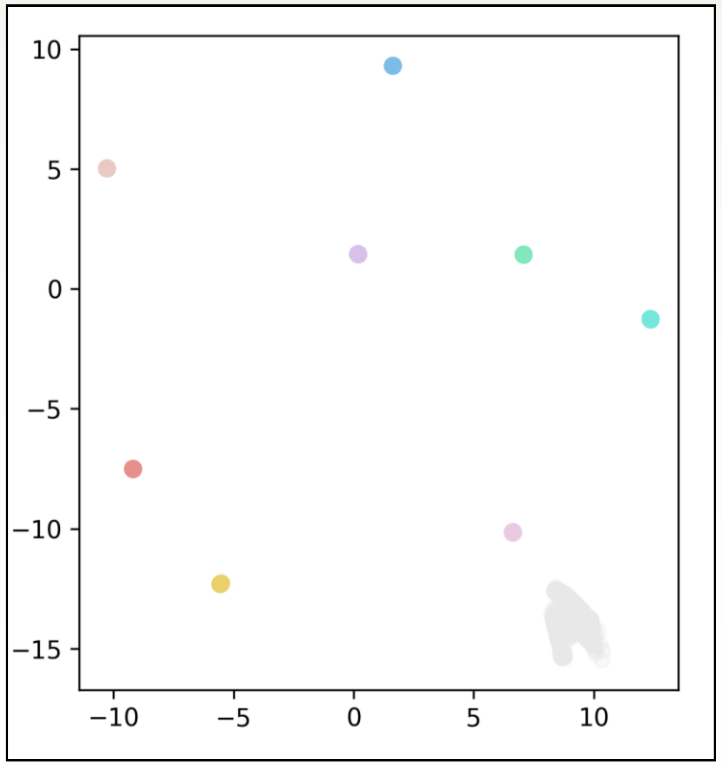
*NB: Removes saddle point for large N

JK, paper in prep.

Example on image data





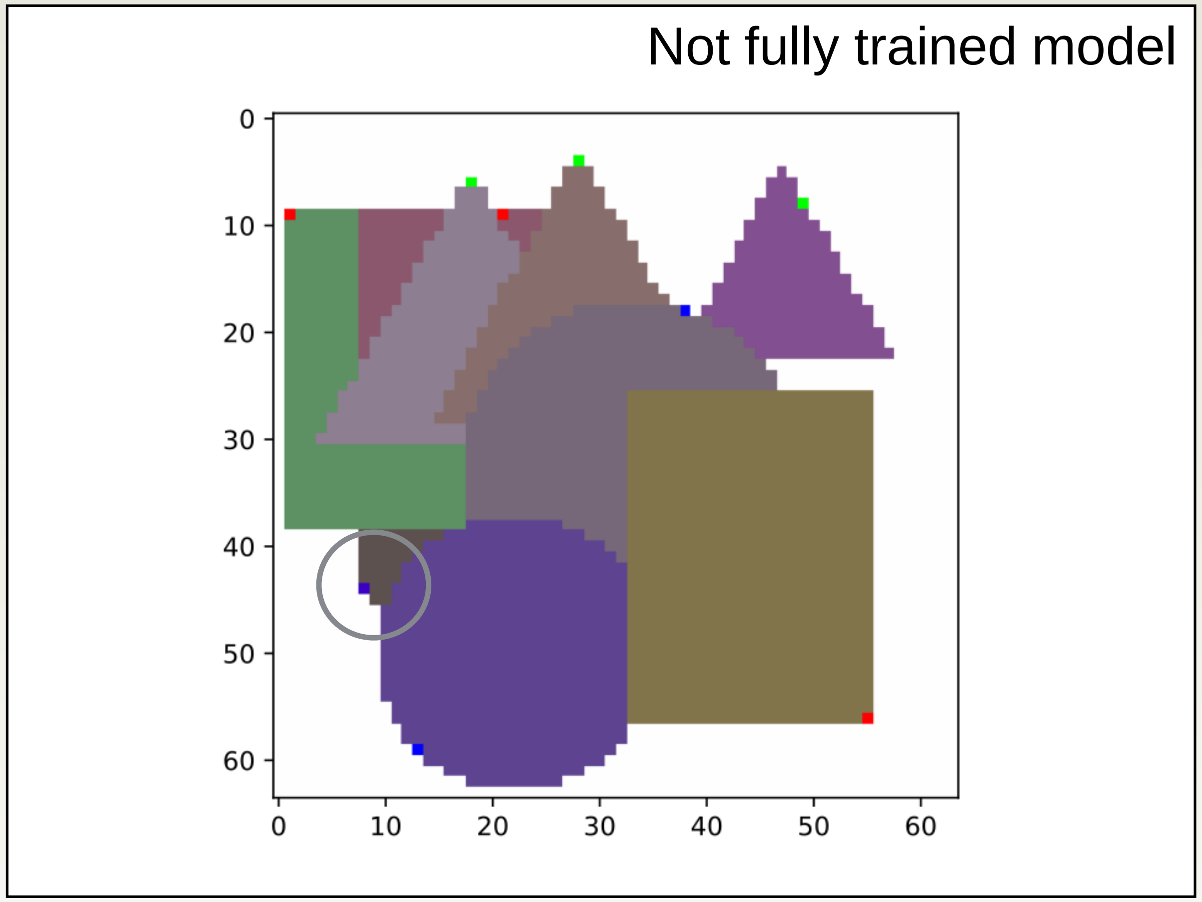


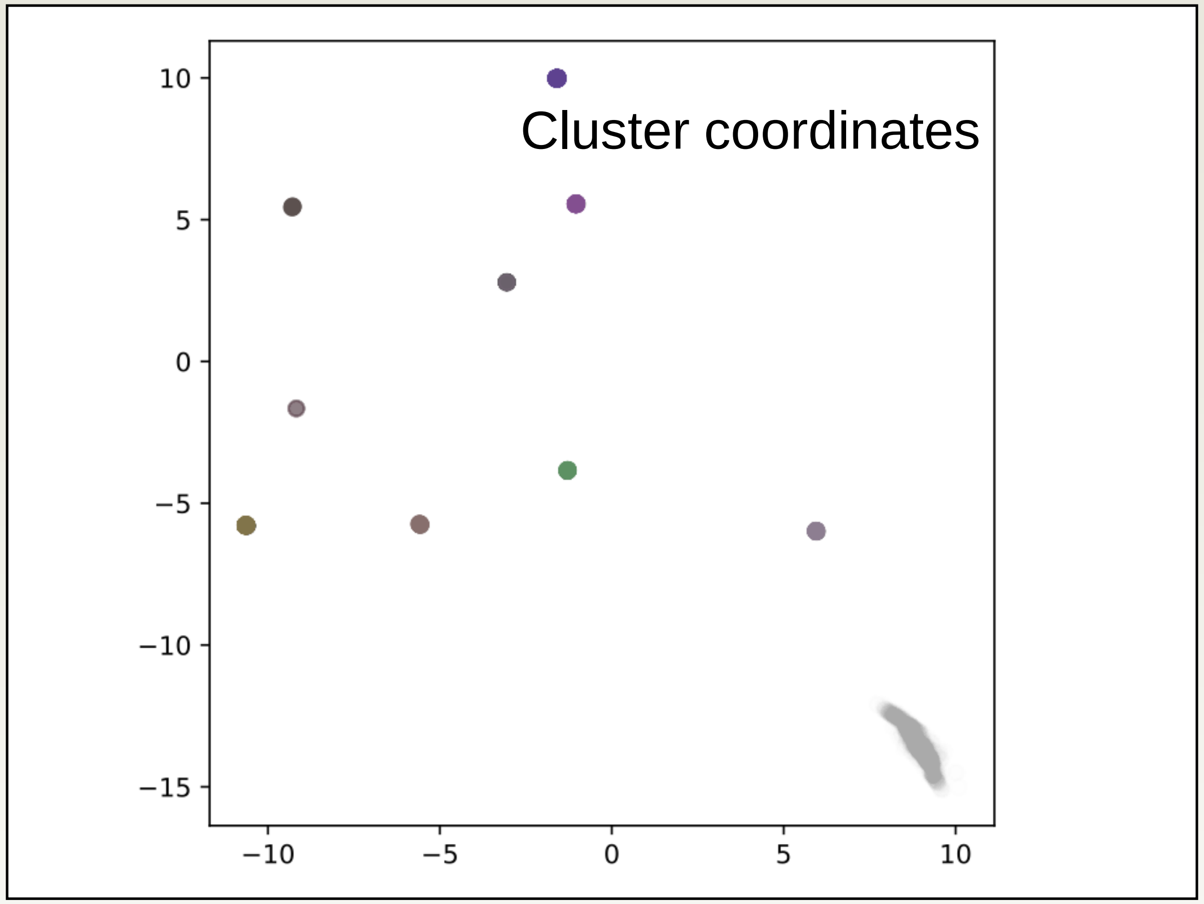
- Proof of principle using images with large overlaps
  - Condensation, object ID
  - Rather simple CNN

- Visualise β_i / β_{max} as alpha value

JK, paper in prep.

Results





- Inference
  - Start with highest β vertex, collect points in $t_d \cong 0.9$
    - Get object properties
  - Repeat until $\beta_{min} \cong 0.1$

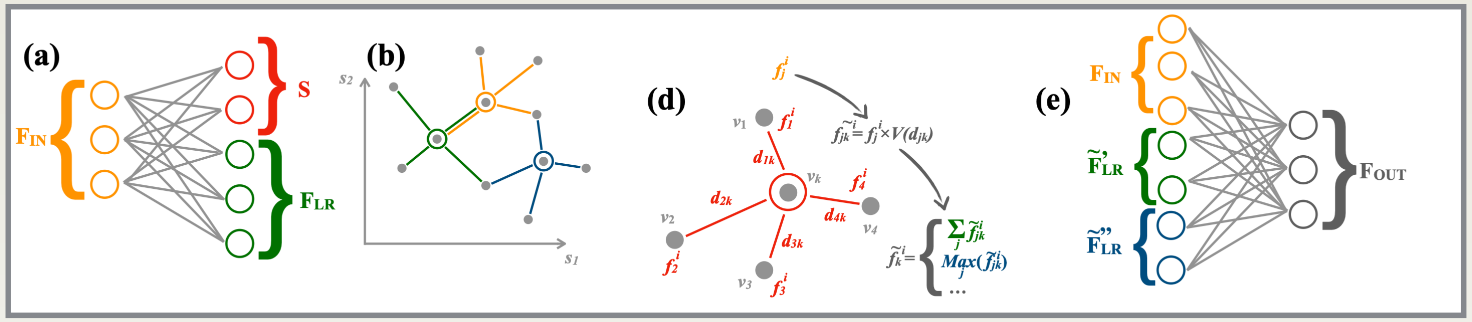
$$\breve{V}_k(x) = ||x - x_\alpha||^2 q_{\alpha k}, \text{ and}$$

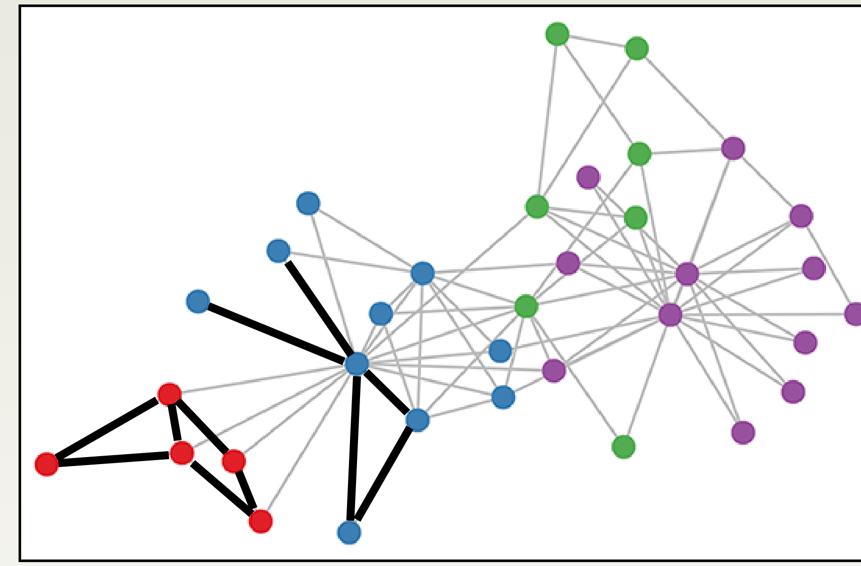
$$\hat{V}_k(x) = \max(0, 1 - ||x - x_\alpha||) q_{\alpha k}.$$

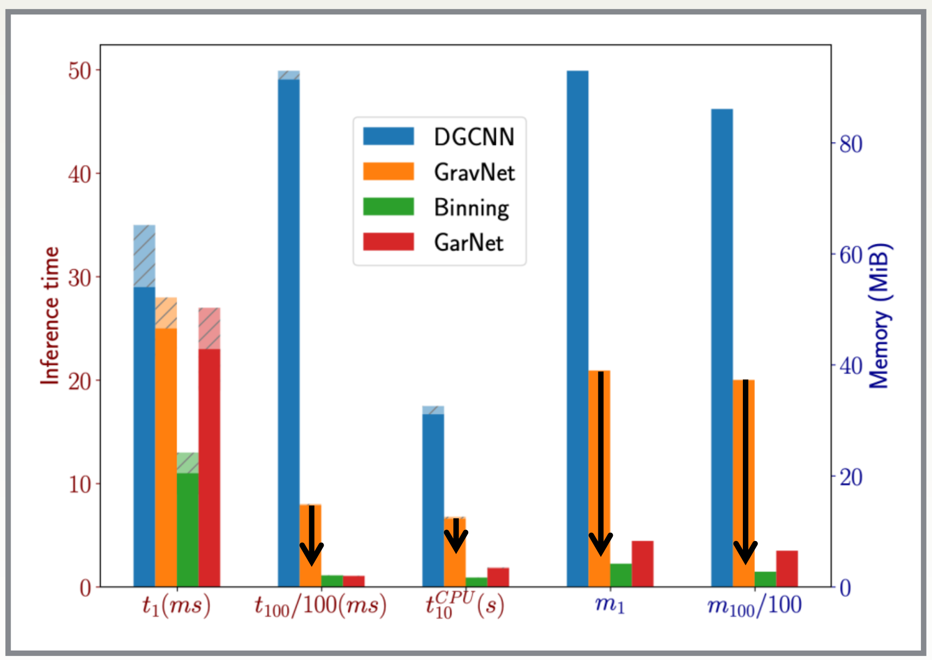
- Object condensation allows to predict K particles from N detector inputs
  - Paves the way for one-stage approaches in reconstruction
  - 'Just' needs to be combined with the networks proven to work well

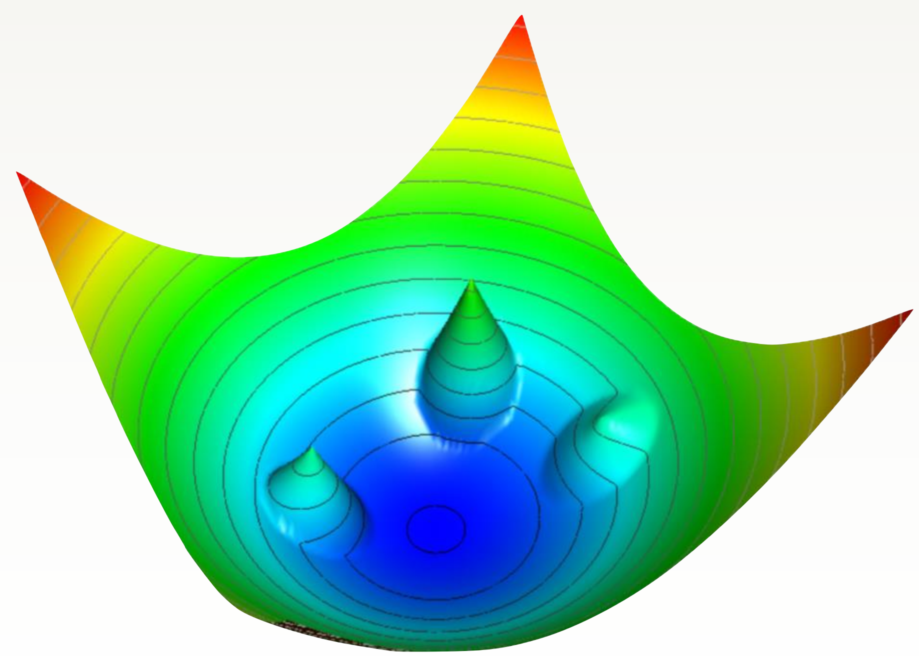
JK, paper in prep.

It all comes together









- All tools at hand
- Near future will be exciting

Summary

- High granularity calorimeters are widely accepted in HEP to control backgrounds, pileup and precise particle flow
- Very promising performance of ML algorithms in high granularity calorimeters
  - Direct link to particle flow
- Pushing forward developments for particle reconstruction
- Pushing forward new machine learning approaches