Calorimeter Reconstruction with Machine Learning
- Focus on Deep Neural Networks -

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based on work within the FCChh barrel calorimeter group, the CMS Collaboration, and with S.R. Qasim, Y.Iiyama, M. Pierini

15.4.2019
Machine learning techniques are very powerful for pattern recognition and pattern generation (see Sofias talk)
Can be applied to complex and smeared-out problems (finding cats in an image)
Intrinsically high potential for parallelisation (fast)
Outline

1) Hits → Energy (single particles)

Energy reconstruction

Particle Flow, pileup suppression

Shower separation

Shower identification

Software Compensation etc
Outline

1) Hits $\rightarrow$ Energy (single particles)

- Energy reconstruction

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Shower identification

2) Single Particle ID In Pileup
Outline

1) **Hits → Energy** (single particles)

2) **Single Particle ID**
   - **In Pileup**

3) **Segmentation of overlapping showers**
   - as basis for applying 1) and 2)

**Energy reconstruction**

**Shower separation**

**Shower identification**

**Software Compensation etc**

**Particle Flow, pileup suppression**
Energy Reconstruction: FCChh barrel

- Liquid argon calorimeter
  - ECal: 8 layers, granularity, approx 0.01 in eta, phi
  - HCal: 10 layers, create pixels with approx 0.02 in eta, phi

- For each part: 3D pixels that can be fed to a CNN
  - Set fixed $\eta = 0.27$
  - Store energy and layer number as ‘colours’
  - Set image centre to energy centre of all calo hits
  - Select only hits with $\Delta R = 0.17$ around center

- Aim at charged pion energies (most challenging)
  - Uses 8M events for training
DNN Structure and Results

- **Basic DNN architecture idea:**
  - Feed through energy sum
  - Add small correction to it based on local topology (ResNet-like)
  - Combine to lower granular 3D image and repeat
  - Not an “off-the-shelf” CNN

- **Strong shower-by-shower software compensation capabilities**
  - Also effectively compensates pileup effects
• New CMS endcap calorimeter planned for High-Luminosity LHC

• To cope with HL-LHC radiation and 200 PU

• Silicon and scintillator sensors
• Sensor size/area changes with z, x, y
  ‣ From about 0.5cm² hexagons to 10 x 10 cm² tiles
  ‣ Physics based
  ‣ Problem for CNNs
Energy Reconstruction: CMS HGCal

‘brute force’ solution:
- Chose rather coarse pixelisation
- Per sensor information
- Build pixel “colours” with a small dense, translation invariant network (1x1x1 CNN)
- Feed to ‘standard’ CNN architecture

- Resolution for hadrons about factor 2 better than standard clustering
Single Particle ID

- Classify individual particle types
  - HGCal: electrons, photons, muons, charged pions
  - FCChh: electrons, photons, muons, charged/neutral pions

- Use CNNs similar to the ones for energy reconstruction
  - Multi-class discriminants

- Strictly local: does not use explicit track information (although it could)
• Detectors are usually not a regular grid
• ‘brute force’ solutions have limitations

➡ Need more geometry ‘aware’ structures
➡ Shower separation requires full granularity (sensor energy fraction association)
Shower Separation: Going beyond CNNs

- Using graph neural networks for reconstruction
  - Invariant w.r.t. order of inputs
  - Do not depend on a regular geometry
  - In particularly interesting: **dynamic graph networks** learning space transformations (e.g. local energy density taking into account sensor geometries)

- Here in a simplified irregular calorimeter

- 2 overlapping charged pion showers

Already show features to be reconstructed by full particle flow..
• Developed new GNN architectures in context of clustering: GarNet (fast) and GravNet (high purity)
  ‣ Distance weighted, learning space transformations

• Basic idea: every shower/track is Gaussian in a sufficiently transformed space

• Loss function (to be minimised during training) aims to reconstruct each individual shower
  ‣ Mild energy weighting of hits

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

• Consider charged pion showers, 10-100 GeV

• Also compare to a CNN-based approach ("binning")

S.R. Qasim, JK, Y. Iiyama, M. Pierini; arXiv:1902.07987, in review by EPJC
• Use distances to visualise perception of the DNN
  ‣ Here GravNet

• Showers are successfully reconstructed
  ‣ Connecting **tracks** are identified
  ‣ EM/hadronic components are **linked**
  ‣ Fractions are separated

S.R. Qasim, JK, Y. Iiyama, M. Pierini; arXiv:1902.07987
Quantitative Results

- Focus on the overlap region, only (20-80% overlap)
- Define energy response
  \[ R_k = \frac{\sum_i E_ip_{ik}}{\sum_i E_it_{ik}} \]

- The graph network based approaches outperform the CNN approach
- The GravNet model outperforms all approaches
- **GravNet** better performing and lower resource requirements than proposal from literature (DGCNN)

- **GarNet** very fast, developed with trigger application in mind
  - CNNs profit from highly optimised code and show worse performance and adaptation power to irregular geometries

S.R. Qasim, JK, Y. Iiyama, M. Pierini; arXiv:1902.07987
• Deep Neural Networks are very powerful tools for reconstruction
  ‣ Energy determination
  ‣ Identification
  ‣ Separation (aka clustering/tracking)

• Graph based approaches are completely independent of any regular grid and explicit detector geometries
  ‣ Tracking and calorimeter clustering become basically the same task, and can be described in a common framework

• DNNs are highly parallelisable
  ‣ Very interesting for trigger applications on dedicated hardware

Tensorflow & Keras implementation
https://github.com/jkiesele/caloGraphNN