Energy Reconstruction for a Hadronic Calorimeter Using Neural Networks

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Outline

- Introduction
- Experimental Setup
- Energy Reconstruction
- Results
- Conclusions
Introduction

- Reconstruct the energy scale for hadrons
  - calorimeters often are non-compensating (e/h \neq 1)
    - degradation of response to hadrons - non-linearities arise
  - minimization of the energy resolution
  - recover linearity
- Use of experimental data from beam tests with the hadronic calorimeter of ATLAS - Tilecal
Introduction (cont.)

- A neural network was chosen for energy reconstruction
  - can perform complex input/output mappings
  - good generalization capabilities
- Comparison to the classical weighting techniques (H1 inspired)
Experimental Setup

• Prototype module of Tilecal was tested
  • 5 old Tilecal modules were placed around it
• Eight different pion beam energies were acquired
  • 20, 50, 80, 100, 150, 180, 300, 400 GeV
• One $\eta$ point was used (-0.35)
Experimental Setup (Cont.)
Energy Reconstruction

- Energy deposited in the calorimeter cells was used to perform the reconstruction
- classical methods divide the energy cell space in several bins
- the neural network uses the cell information or sum of cells without binning
- The H1 method minimizes the following function:

\[ \varepsilon^2 = \frac{1}{N} \sum_{i=1}^{N} (E_{rec_i} - E_{beam})^2 + \lambda \frac{1}{N} \sum_{i=1}^{N} (E_{rec_i} - E_{beam}) \]

\[ E_{rec_i} = \sum_{j=1}^{13} w_j \times E_{cell_{ij}} + b \times E_{old} \]
Results

- Two main measurements are used to determine the energy reconstruction quality:
  - non-linearity and energy resolution ($\sigma/\mu$)
- No corrections (raw data):
  - noise cuts are applied to all cells
  - non-linearity $\rightarrow$ 2.2%
  - energy resolution $\rightarrow$ 
    \[
    \frac{\sigma}{\mu} = \frac{(54.4 \pm 0.8)\%}{\sqrt{E}} + (7.13 \pm 0.05)\% + \frac{6}{E}
    \]
Raw data
Results (H1 method)

- All cell's energies are plotted in one histogram
  - divided into bins -> 13
- Minimization is performed for each energy using the formula shown before
Results (H1 method)

- Weights are parametrized with respect to the cell bins
- The results are parametrized again with respect to the beam energy
- During operation beam energy is not known *a priori* - iterations needed to converge
- Non-linearity -> 1.3 %
- Energy resolution -> \[ \frac{\sigma}{\mu} = \frac{(40.8 \pm 1.2)\%}{\sqrt{E}} + (5.30 \pm 0.08)\% + \frac{6}{E} \]
H1 method
done by Santiago Gonzalez
Results (neural network)

- Input data were normalized by a constant multiplier

- Neural network desired output:

\[
\begin{align*}
\mathbf{d}_{nn}(i, n) &= \left[ \frac{\mathbf{e}_{sum}(i, n)}{\mathbf{e}_{mean}(i)} - 1 \right] \times \alpha(i) \times \mathbf{e}_{beam}(i) + \mathbf{e}_{beam}(i) \\
\mathbf{e}_{sum}(i, n) &= \sum_{k=1}^{N_{inputs}} \mathbf{e}_{input}(i, n, k) \\
\mathbf{e}_{mean}(i) &= \frac{1}{N_{events}} \sum_{n=1}^{N_{events}} \mathbf{e}_{sum}(i, n) \\
\mathbf{\mu}_{nn}(i) &= \frac{1}{N_{events}} \sum_{n=1}^{N_{events}} \mathbf{d}_{nn}(i, n) = \mathbf{e}_{beam}(i) \\
\mathbf{\sigma}_{nn}(i) &= \alpha(i) \times \frac{\mathbf{\sigma}_{raw}(i)}{\mathbf{\mu}_{raw}(i)}
\end{align*}
\]
Results (neural network)

- Feedforward network: two hidden layers (14-7)
- Better results for the lower energy range
- Standard backpropagation learning was used
- Non-linearities of 0.42% and 0.75% were achieved for the training and test set, respectively

- Energy resolution for the training set:

\[
\frac{\sigma}{\mu} = \frac{(47.7 \pm 1.4)\%}{\sqrt{E}} + (4.74 \pm 0.14)\% + \frac{6}{E}
\]
Results (neural network)

\[ N\text{Noutput} , \quad \frac{\sigma}{\mu} = 6.0\% \]

\[ \text{Raw data} , \quad \frac{\sigma}{\mu} = 6.7\% \]
Neural Network
Conclusions

• A neural network was applied to reconstruct the energy scale of hadrons for the Tilecal calorimeter

• improve both linearity and energy resolution

• Recovery from non-linearity is considerable

<table>
<thead>
<tr>
<th></th>
<th>Non-linearity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Raw</td>
<td>2.2</td>
</tr>
<tr>
<td>H1</td>
<td>1.3</td>
</tr>
<tr>
<td>Neural Net.</td>
<td>0.42</td>
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</table>
Conclusions

- Energy resolution:

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- Neural network - no need for energy estimation or iterations

- Other $\eta$ points are under investigation