Dual-Readout Calorimetry Signal Analysis with Neural Networks

Murali Saravanan
Overview

- Dual-Readout Calorimetry Recap
- Current Results
  - Part I: Monte Carlo Simulations
  - Part II: Real Data
  - Part III: hls4ml
- Future Steps
The LHC and Calorimetry

• Calorimeters are responsible for energy measurement in ATLAS, CMS, and various particle detectors

• Hadronic and Electromagnetic Calorimetry
  - protons, pions, and fragmenting quarks and gluons
Hadronic Calorimetry

• Measure em and non-em components
  • Huge fluctuations in em component (up to 40%) on event-by-event basis

• Different calorimeter materials respond to em and non-em differently. Use response curves but this works on average
Dual Readout Calorimetry Recap

• Measure both Cerenkov and Scintillation radiation to achieve em energy resolution on event-by-event basis
  • Amount of Cerenkov/Scint light can be tweaked by materials and geometry of physical calorimeter

• Huge improvement for hadronic energy resolution, would be useful in future colliders (FCC, ILC, CLIC)
Single Channel Readout?

- Single Channel saves overhead
- Four parameters vary
  1. Ratio of Cerenkov/Scintillation Radiation (Area)
  2. Scintillation Decay Rate
  3. Photoelectron Count
  4. Digitizer Freq/Bin Number
Using NN

• NN is constant time
• Predict two parameters
  1. Cerenkov pulse area
  2. Scintillation pulse area

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Total params: 1,032
Trainable params: 1,032
Non-trainable params: 0
Part 1: Monte Carlo
Simulated Data
Monte-Carlo Generation of Data

• Modify:
  • Ratio
    • 10-> 10x more area of Cerenkov than Scintillation
    • -10-> 10x more area of Scintillation than Cerenkov
  • Scintillation Decay
  • Photoelectron Count
  • Binning

• Generate a library of histograms, varying the above parameters to create different experiments
• Create many events per experiment to create needed random fluctuations
Example Pulse

- Vary Ratio between -25 and 25
- Vary Scint Decay from 15ns to 50ns
- 1k-5k photoelectrons
- 30, 100, 300 bins
- Vary digitizer freq and photostatistics
- 30 bins, 5k
Part I Conclusions

• Major dependence is on ratio and not scintillation decay time
• Higher photoelectron count gives better results
  • Gradual change over 1k-5k photoelectrons range (no tipping point)
• Higher digitizer freq ≠ better prediction
  • Low freq hides the effects of fluctuations
• Scintillation prediction is much more stable than Cerenkov prediction
Part 2: Real Data

Dual Cherenkov and Scintillation Response to High-Energy Electrons of Rare-Earth-Doped Silica Fibers

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Real Data

• response of Ce-doped silica fibers exposed to electrons in the 20–200-GeV

• What does a realistic pulse look like? What is the actual ratio of C/S? Expected photoelectron count?
Average Pulse

200 GeV Pulse

[... graph information ...]

FIG. 6. Average pulse shape normalized to the number of events for Ce:SiO₂ fibers for a 20-GeV electron beam (left panel) and a 150-GeV electron beam (right panel). Back and front read-out are compared. The dashed lines are guides for the eye. phe, photoelectrons.

Photoelectron Count

- 7.5k for Cerenkov, 30k for Scintillation (ratio=-4)

Monte Carlo results in this area

• With 5,000 photoelectrons and 100 bins, possibility of less than 1% error
Real Data NN

• In progress!
• Need to consistently clean data
Part 3: Implementation on FPGAs
Intro to FPGAs

• Multiplier Units
  • Does arithmetic
• Flip Flops
  • Short term memory registers

• Wire algorithms into board
• High Level Synthesis (HLS) is the language that Xilinx FPGAs use
hls4ml

• Takes NN and creates HLS implantation that provides resource usage estimates

• Up to 6,000 parallel operations=# of multiplication units=max # of nodes and weights in NN if we aim for one clock cycle per analysis

• Can trade latency for lower resource usage

Preliminary Results

• 100 bin Model with 5ns goal
Preliminary Results

• hls4ml in general provides an overestimate of resource usage

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• Can prune unnecessary nodes from intermediate layer to decrease resource usage
Project Conclusions

• Dual Readout Calorimetry is promising for improving resolution of em-portion of hadronic energy on an event-by-event basis

• Neural Networks can be implemented into FPGAs for low latency inference in single channel dual readout calo
  • Small networks are adequate

• Simulated performance of NNs can be used to inform the geometry/construction of the calorimeters and the associated hardware
Project Conclusions

Single Channel Dual Readout Calorimetry can work thanks to Neural Networks
Future Steps

• Produce NN results on real data
• Look at implementation on real FPGA
Questions?