



Smart pixel sensors Towards on-sensor filtering of pixel clusters with deep learning

Jieun Yoo, Jennet Dickinson, Morris Swartz, Giuseppe Di Guglielmo, Alice Bean, Douglas Berry, Manuel Blanco Valentin, Karri DiPetrillo, Farah Fahim, Lindsey Gray, James Hirschauer, Shruti R. Kulkarni, Ron Lipton, Petar Maksimovic, Corrinne Mills, Mark S. Neubauer, Benjamin Parpillon, Gauri Pradhan, Chinar Syal, Nhan Tran, Dahai Wen, Aaron Young

University of Illinois Chicago, Fermi National Accelerator Laboratory, Johns Hopkins University, Northwestern University, University of Kansas, The University of Chicago, Oak Ridge National Laboratory, University of Illinois Urbana-Champaign

Silicon pixel detectors

- Experiments at colliders typically have a silicon pixel detector at the center
 - Concentric rings tiled with sensors
- Silicon sensors are depleted of charge carriers by high voltage
- When a charged particle from a collision passes through, it creates e/h pairs
- Charge is read out and transferred off-detector
 - Charge cluster information is used for physics analysis offline







https://cms.cern/detector

Particle tracks and vertices

- Connecting the dots between charge collected in different pixel layers creates a particle track
 - Detector should be low-mass so interactions in inactive materia doesn't disrupt this trajectory
- Solenoid magnet immerses the pixel detector in a magnetic-field, causing tracks to curve
 - □ Very curved \rightarrow low transverse momentum (low-p_T)
 - □ Almost straight \rightarrow high transverse momentum (high-p_T)
- Reconstructing vertices is critical
 - Secondary vertices help identify particles: long, short, medium lifetime?







Survey of Big Data sizes in 2021



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Designing hardware for the LHC is challenging

- □ LHC/CMS produces a lot of data
 - □ New data every 25 ns (p-p collision)
 - Physicists have to throw most of it away
 - Physically and financially challenging
 - Risk to throw away significant information
- Detector is continuously being sprayed with particles
 - Need radiation tolerant on-detector electronics
- High voltage and low temperature requirements
 - □ Up to -800 V, -35 C







Goal of the Smart Pixel team

- On-chip data filtering at rate (40 MHz)
- Al algorithms
- Reconfigurable algorithms
- Hybrid pixel detector
 - Silicon sensor
 - Pixelated ROIC
 - □ Analog front-end + ADC
 - Al in digital logic



Sensor geometry, charge clusters, and profiles



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Neural network classifier (filter)

- Inputs are cluster images projected onto y-axis and the associated y₀
- Three output categories
 - □ high-momentum (> 200 MeV)
 - low-momentum, negatively charged
 - Iow-momentum, positively charged
- Simulated dataset of 800,000 clusters
- □ Classical training and testing set split 80%-20%
- Tensorflow/Keras, 200 epochs for training, 20 epochs of early stopping, 1024 batch size, Adam optimizer





Neural-network design space exploration

- □ Three models of increasing complexity
 - Model 1
 - \Box Two input features: **cluster y-size** and position y₀
 - □ Single dense layer, 128 neurons, 771 parameters
 - Model 2
 - **u** 14 input features: **cluster y-profile** (13) and position y_0
 - Single dense layer, 128 neurons, 2,307 parameters
 - Model 3
 - □ 105 input features: **cluster y-profile** at 8 time instants (13 x 8) and position y₀
 - CNN (time-lapse picture), 83,331 parameters

Model	Sig. efficiency	Bkg. rejection
Model 1	84.8~%	26.6~%
Model 2	93.3~%	25.1~%
Model 3	97.6~%	21.7~%

→ Hardware implementation

Bandwidth saving 54.4% - 75.4%



HLS-based hardware design flow



Neural-network hardware co-design (model inputs)

- Input quantization
 - The charge collected by the analog readout goes through an ADC
 - □ 2-bit quantization for the y-profile
 - Ranges of collected charges
 - \Box y₀ coordinate on 6 bits
 - G4 bins of 250 μm width

ADC output	Charge interval $[e^-]$
00	< 400
01	400 - 1600
10	1600 - 2400
11	> 2400





Neural-network hardware co-design (model weights)

Model quantization

- Quantization-aware training with QKeras
- □ Model "inspired" on the previous design space exploration
 - Extra dense layer
 - Batch normalization (~Dropout) prevent overfitting in training
- **5** bits for weights, 10 bits for activation provides best results





Neural-network hardware co-design (optimizations)

- Goal: reduce area
 - Batch-normalization folding
 - Neurons reduction
 - Weights & activation bit-width reduction
 - $\Box \quad Softmax \rightarrow Argmax$





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Neural-network hardware co-design (optimizations #2)

- **D**rop y_0 as a feature and use a region-specific implementation
 - □ 13 different models provide altogether better performance
 - □ We can leverage weight reprogrammability



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ROIC integration

Integration of the ML algorithm as digital logic with the analog front-end into the in the pixelated area (ROIC)



Low-power 28nm CMOS

- Early power estimates for the digital logic
 - $< 300 \ \mu W$



Reprogrammable weights distributed across the matrix (highlighted in white)



Where we are now

- Tapeout of the current classifier algorithm (**filtering**)
- □ Moving to **compression** (or **featurization**)
 - Train algorithms to extract properties of the incident particles
 - Read this information out instead of raw (filtered) data



🚰 Fermilab

Thank you



