FERMILAB-SLIDES-24-0170-CMS

Smart Pixel Sensors for the HL-LHC

New Perspectives
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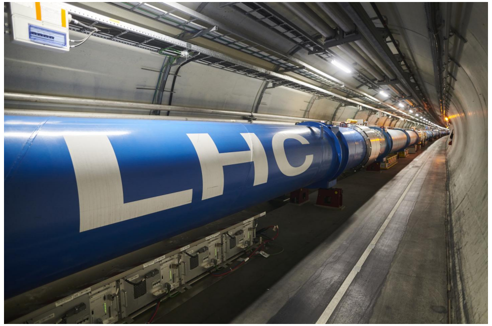
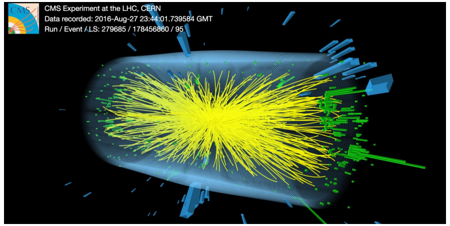
Motivation

- LHC upgrade requires technologies to deal with an increase in luminosity, pileup, & data, in a high radiation-environment
- LHC pp collisions occur at 40MHz, are selected by a trigger to read out events ~ 1MHz
- Currently, pixels are limited by readout bandwidth, so they are not in the trigger; e.g., events with new physics only in the pixel data are not selected at all
- AI *embedded* on a chip can be used to filter data at the source, enabling data reduction AND taking advantage of pixel information to enable new physics measurements and searches



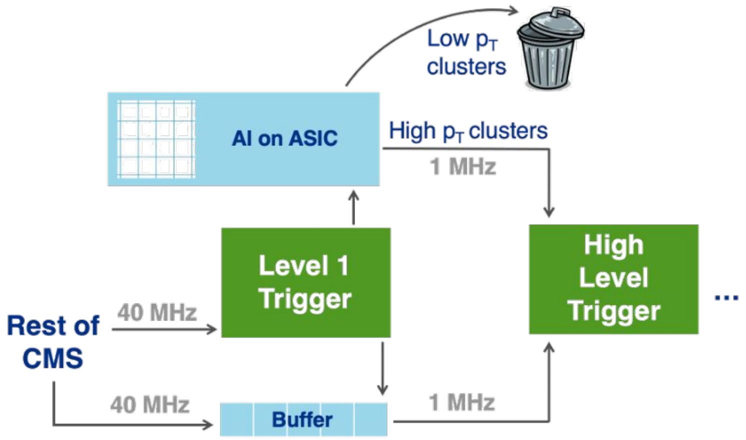
LHC Luminosity

- LHC design 10^{34} cm^{-2} s^{-1}
- LHC Runs 2/3: 2 x LHC
- HL-LHC: 5 to 7 x LHC



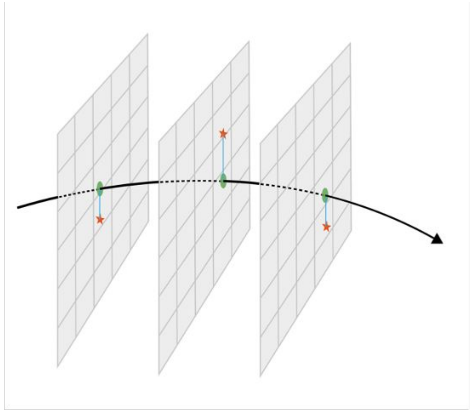
Data reduction

- Data reduction through
  - **Filtering** through removing low p_T clusters
  - **Featurization** through converting raw data to physics information
- Combination of approaches can reduce data rate enough to use pixel information at Level 1

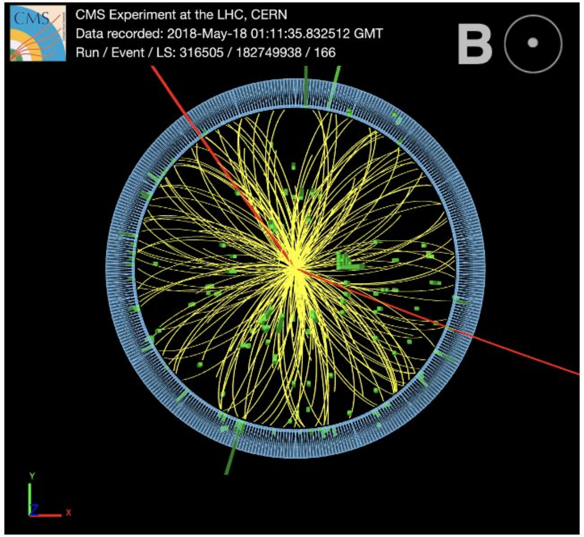


Cartoon created by J. Dickinson

Particle tracks



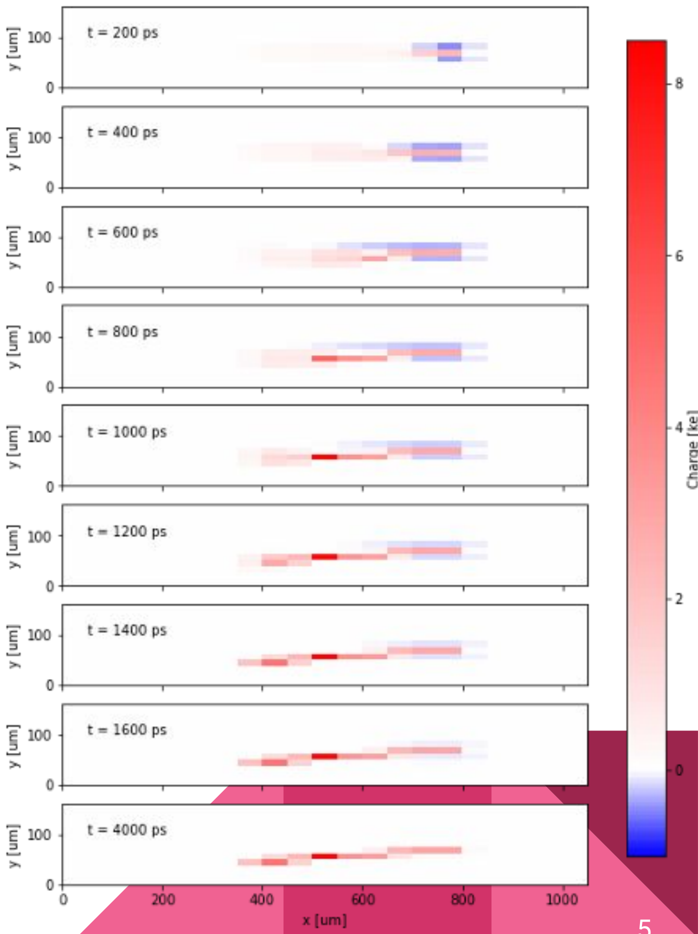
- Connecting the dots between charge collected in different pixel layers creates a particle track
- Solenoid magnet immerses the pixel detector in a B-field, causing tracks to curve



Very curved → low momentum
Almost straight → high momentum

Simulated dataset (link)

- Simulated charge deposition from pions
  - Initial conditions = fitted tracks from CMS
  - For a range of hit positions, incident angles
- Assume a futuristic pixel detector
  - 21x13 array of pixels
  - 50x12.5 µm pitch, 100 µm thickness
  - Located at radius of 30 mm
  - 3.8 T magnetic field
  - Time steps of 200 picoseconds

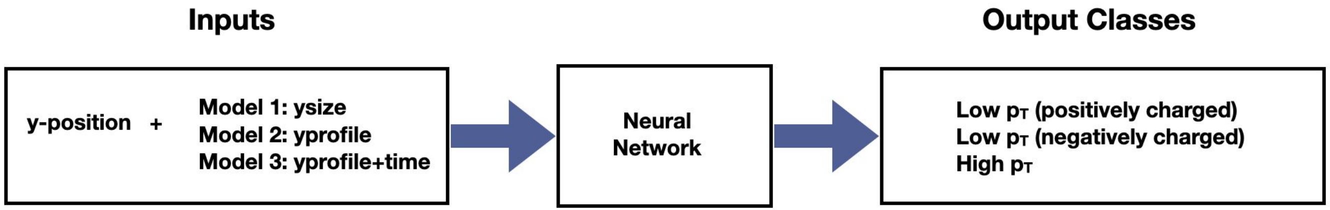


Classification Goals

- Keep as many high p_T clusters as possible for physics
- Decrease data bandwidth

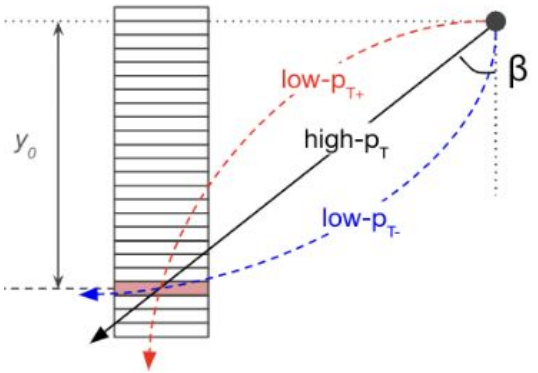
Baseline full precision model

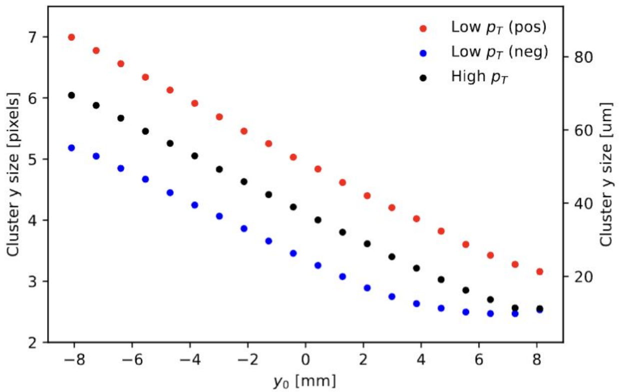
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten (Flatten)            (None, 14)                0

dense (Dense)                (None, 128)               1920

dense_1 (Dense)              (None, 3)                 387

=================================================================
Total params: 2,307
Trainable params: 2,307
Non-trainable params: 0
```



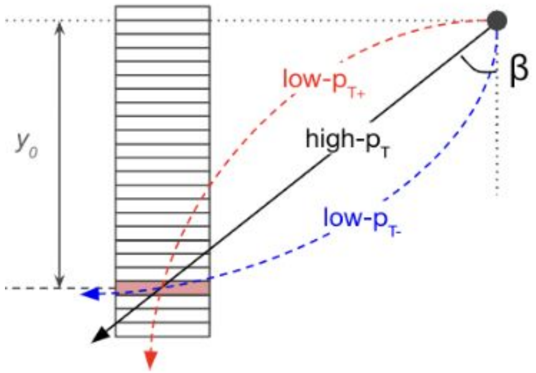
ML Inputs: y-position

- The shape of the cluster is strongly correlated with its y-position (its azimuthal position with respect to the center of the sensor)
- Cluster y-size vs. y-position shows clear correlation between size & position
  - Decrease in cluster size from left to right is due to Lorentz drift
  - The final model chosen uses y-profile (not y-size) due to the former's better performance



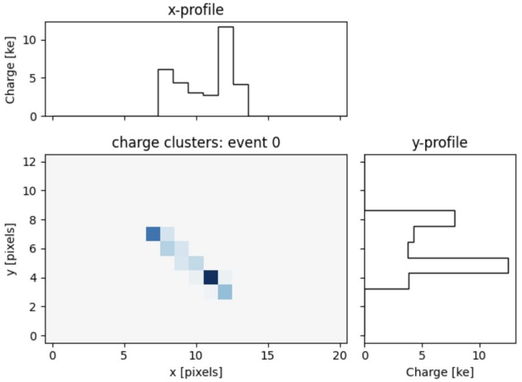


ML Inputs: y-profile

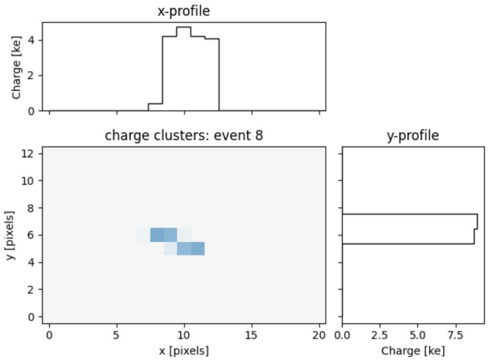


- We use ML due to complicated pulse shapes, and drift & induced currents
- y-profile (sum over pixel rows) projects the cluster shape on the y-axis and is sensitive to the incident angle β and thus the particle's p_T
- x-profile (sum over pixel columns) is parallel to B, and uncorrelated with p_T

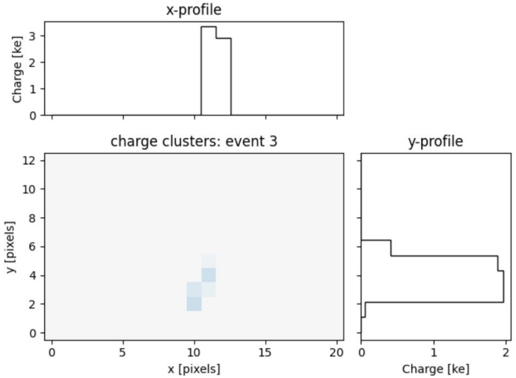
High p_T cluster



Low p_T positively charged cluster



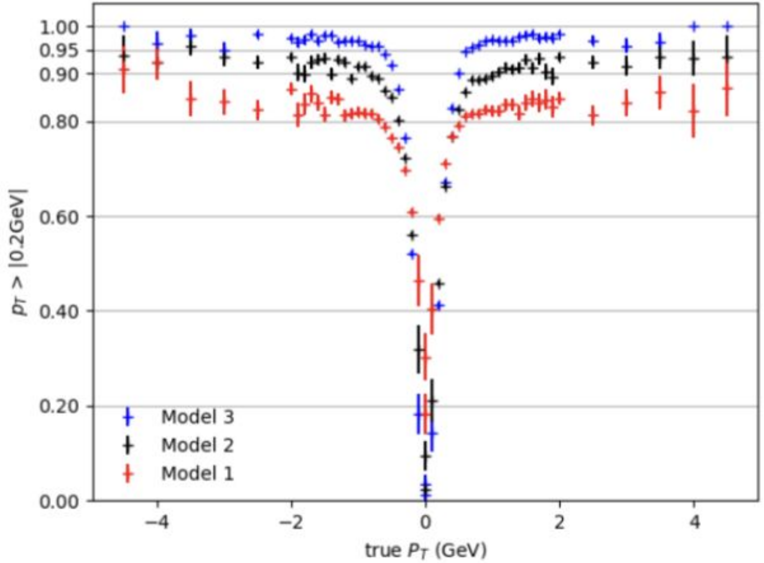
Low p_T negatively charged cluster



Metrics

$$Signal\ Eff. = \frac{\#\ clusters\ classified\ as\ high\ p_T}{\#\ clusters > 2\ GeV}$$

$$Bkg.\ Rej. = \frac{\#\ clusters\ classified\ as\ low\ p_T}{\#\ clusters < 2\ GeV}$$



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

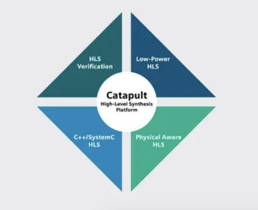
Model 2 was chosen for implementation

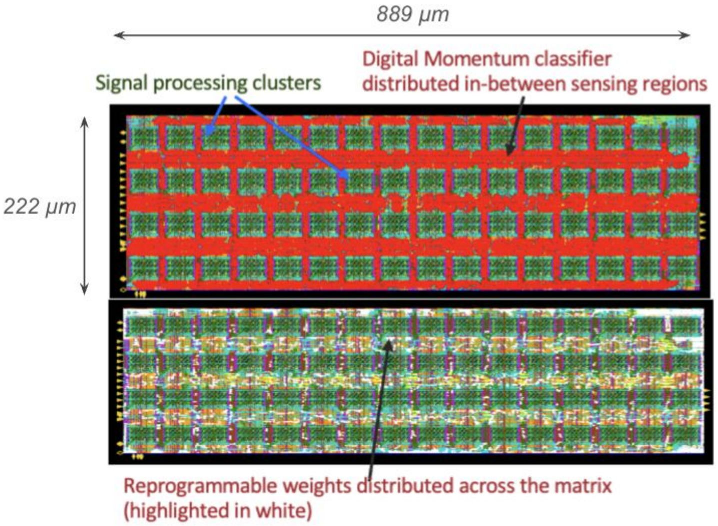
Data Reduction: Estimate 57.1% ~ 75.7%

	Fraction of dataset	Rejection rate
Simulated tracks	40%	37.6 ±1.0%
Multi-pixel untracked	55%	63.2 ±1.1%
Single pixels	5%	100%

On-chip implementation

- Design space optimization & Region specific implementation
    - 13 locally customizable neural network with reprogrammable weights so we can adapt to changing conditions





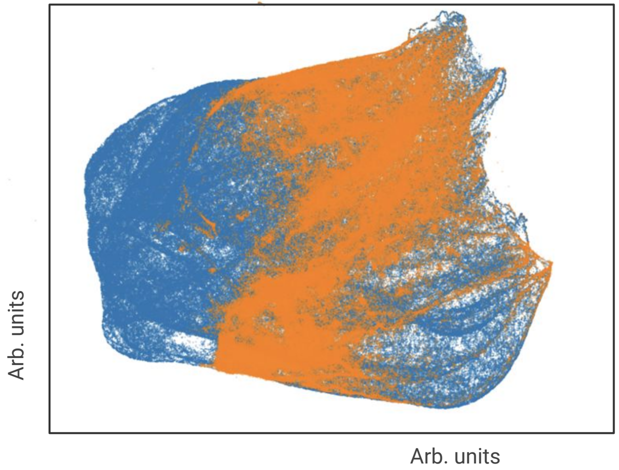
- 4 analog frontends, surrounded by a digital region
- Simulation: 13 x 21; Chip: 16 x 16
- Design expected to operate at < 300 μW
- Area < $0.2mm^2$

Next generation studies: untracked clusters

- The simulated dataset is derived from clusters in CMS that are combined with signatures in other detector layers to form particle tracks
- But, in an example CMS data run, only 40% of clusters are tracked this way
- **~60%** remaining clusters (“untracked”) can result from sources such as very low p_T particles, radiation backgrounds, detector effects
- For our first study, we never specifically trained on these untracked clusters, but still rejected about 63% of them
- The goals of this project is to try to reject more of them

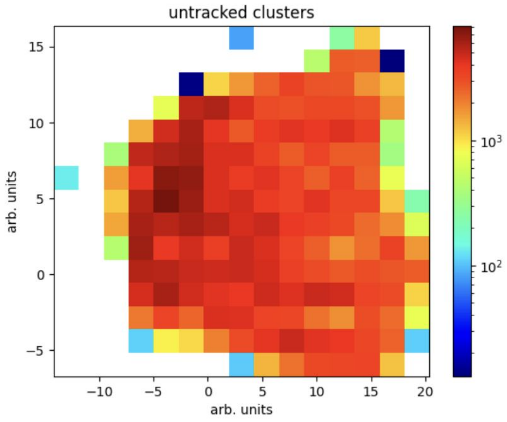
Our idea

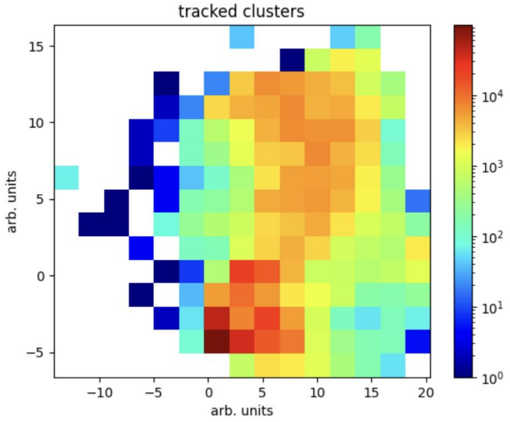
- Use a simple autoencoder to transform tracked and untracked clusters into a 5-dimensional space
- Use UMAP (a dimensionality reduction tool) to help identify tracked vs. untracked clusters, & give us insight on next steps

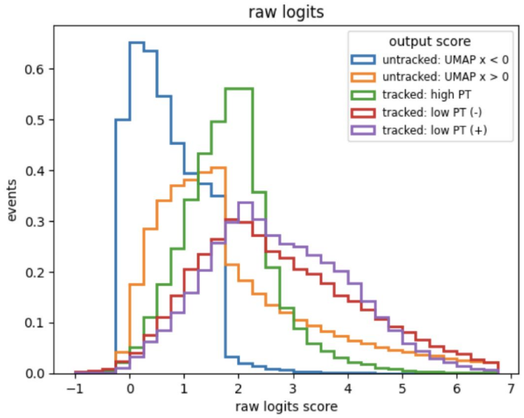


Tracked clusters in orange, untracked in blue

Work in progress







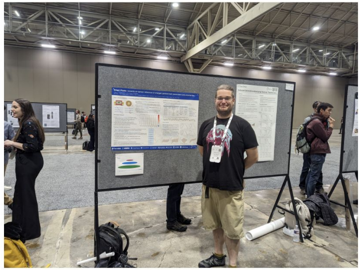
- Untracked clusters are clearly something new data-wise
- Looking at ways to distinguish them, and improve our model

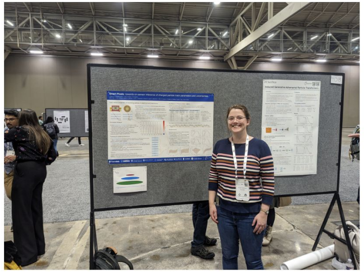
Other on-going work in the group

- Use a regression model to predict angles and positions, and work on designing a v2 version of our chip
- Test our p_T filter chip
- Prepare the way to test our chips with a sensor in a testbeam

Smart Pixels Collaboration

https://fastmachinelearning.org/smart-pixels/





Members

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- **Northwestern University:** Manuel Blanco Valentin
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