



Smart pixels with data reduction at source: possible applications for linear e^+e^- colliders

Jennet Dickinson and Lindsey Gray

International Workshop on Future Linear Colliders

May 17, 2023

jennetd@fnal.gov

The future of particle physics at colliders

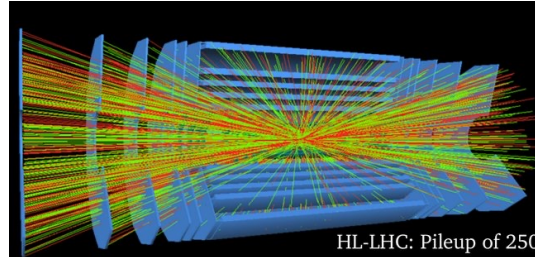
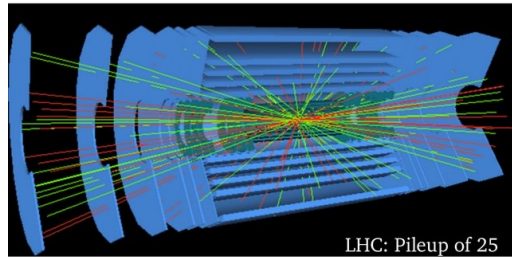
- Detectors with high precision 😊
Smaller pixels, timing capability
- New & upgraded colliders 😊
Higher luminosity, higher energy

The future of particle physics at colliders

- Detectors with high precision 😊 → more readout channels 😞
Smaller pixels, timing capability
- New & upgraded colliders 😊 → more hits, esp. backgrounds 😞
Higher luminosity, higher energy

hh

Higher luminosity → pileup → limitations on trigger & amount of recorded data



Solution!
smart pixels
physics-motivated data
reduction with AI on-ASIC

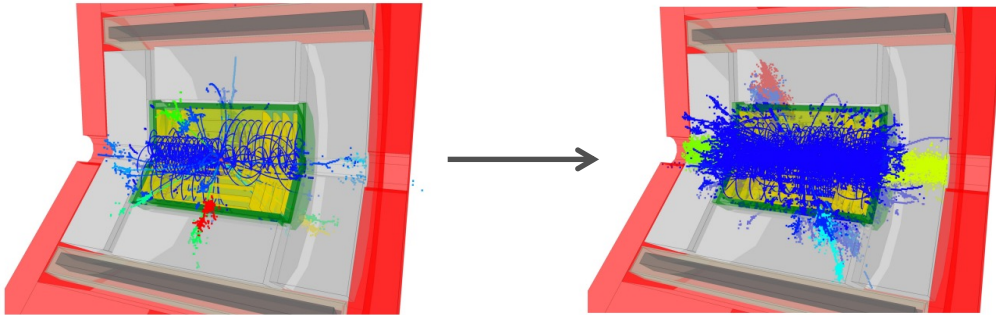
The future of particle physics at colliders

- Detectors with high precision 😊 → more readout channels 😞
Smaller pixels, timing capability
- New & upgraded colliders 😊 → more hits, esp. backgrounds 😞
Higher luminosity, higher energy

hh

ee

Higher energy → more beam background → limitations on detector design



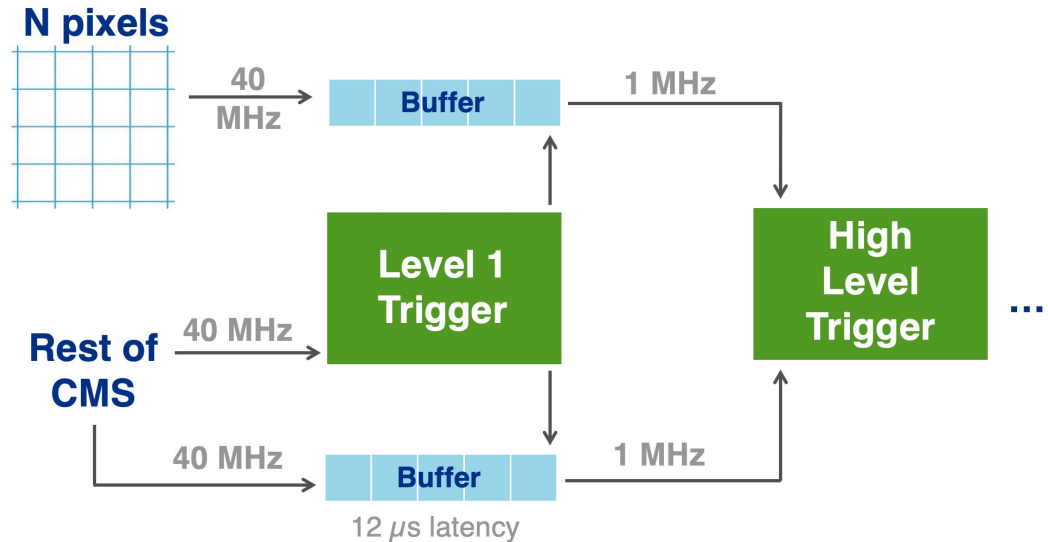
Solution?
smart pixels
physics-motivated data
reduction with AI on-ASIC

Outline

- Smart pixels in the context of the HL-LHC
 - Filtering
 - Featurization
- Applications at linear e^+e^- colliders

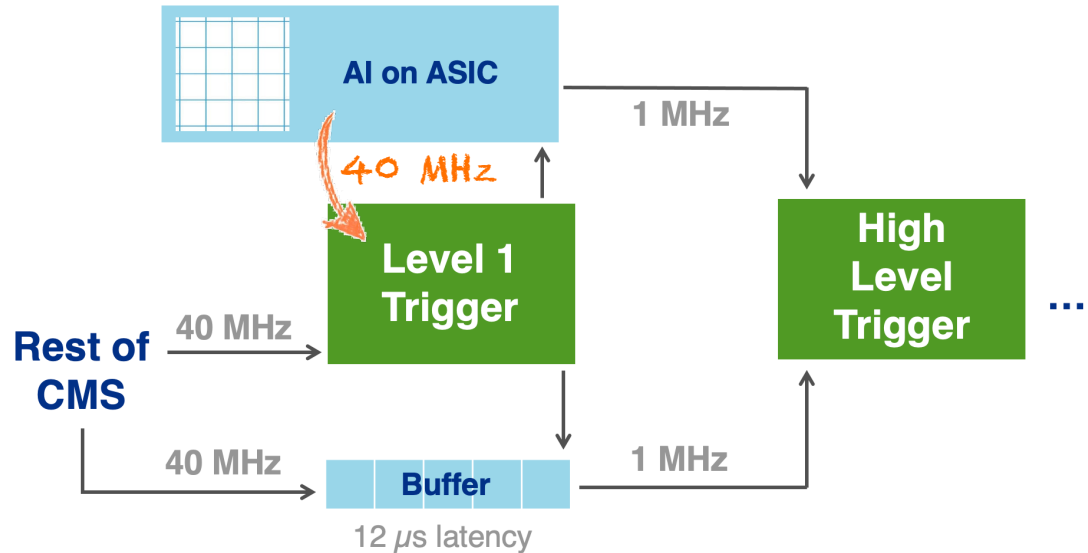
Pixel readout chain: CMS at HL-LHC

- Detector is an array of N pixels
 - 100 x 25 μm pitch
 - 100 μm thick sensor
- Pixel data sits in buffer until L1 decision is made
- Passed to HLT at 1 MHz



Pixel readout chain: our futuristic CMS detector

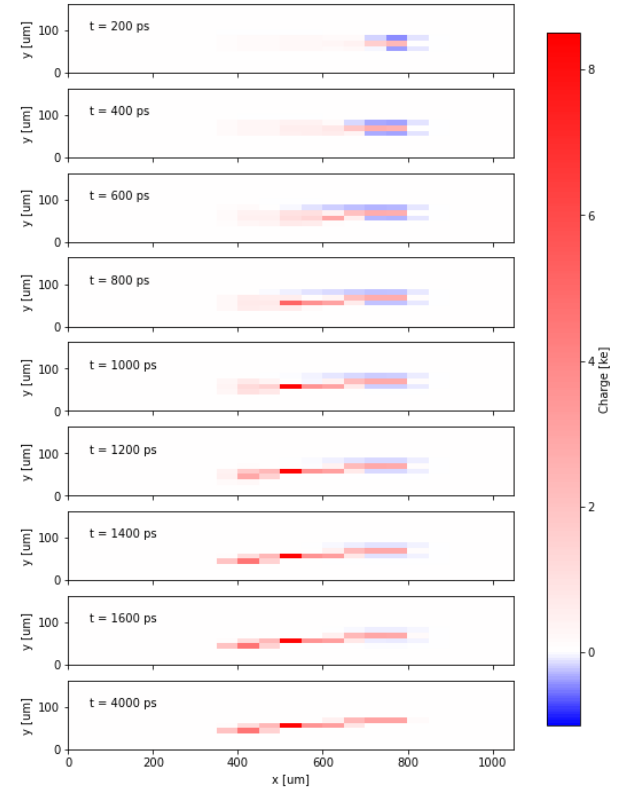
- Detector is an array of **4N** pixels
 - **50 x 12.5** μm pitch
 - 100 μm thick sensor
- **Pixel data is passed to L1 trigger at 40 MHz**
- Passed to HLT at 1 MHz



Can we use smart pixels to transfer
4-160x more data?

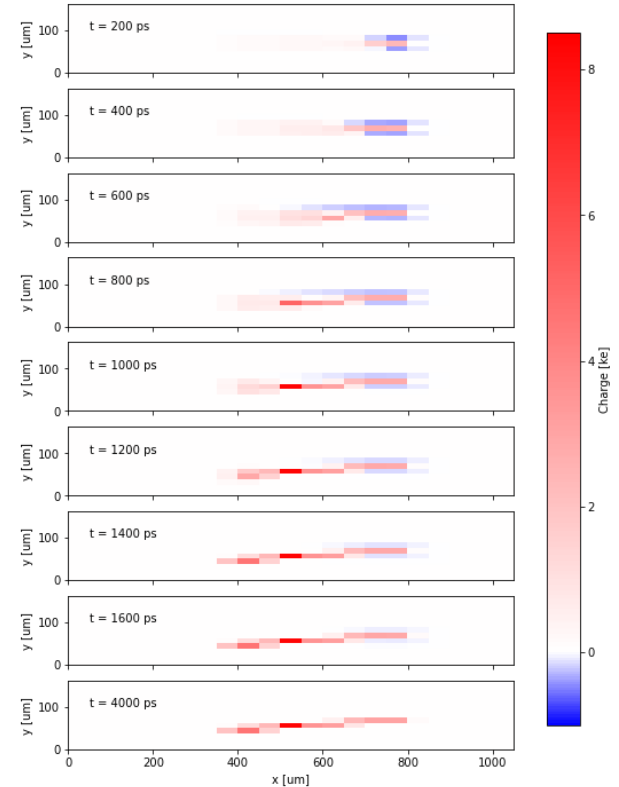
Charged particle signatures in our futuristic detector

- State-of-the-art dataset for developing algorithms for implementation on-ASIC ([link](#))
 - Initial conditions = fitted track params from CMS Run 2 data
- Simulated pions traversing a 21x13 array of pixels
 - 50x12.5 μm pitch, 100 μm thickness
 - Located at radius of 30 mm
 - 3.8 T magnetic field
 - 20 time steps of 200 picoseconds (4 ns total)



Charged particle signatures in our futuristic detector

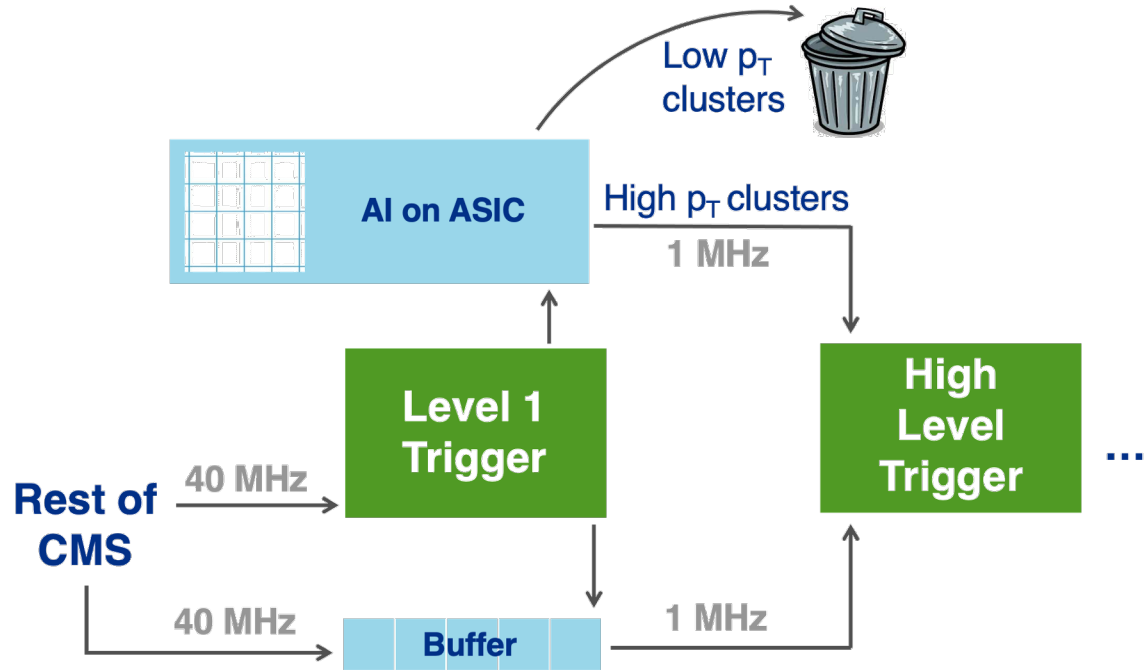
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 - 20 time steps of 200 picoseconds (4 ns total)
- For e^+e^- :
 - Simulation with electrons needed
 - Is signal collected over 4 ns fast enough?



Data filtering on-ASIC

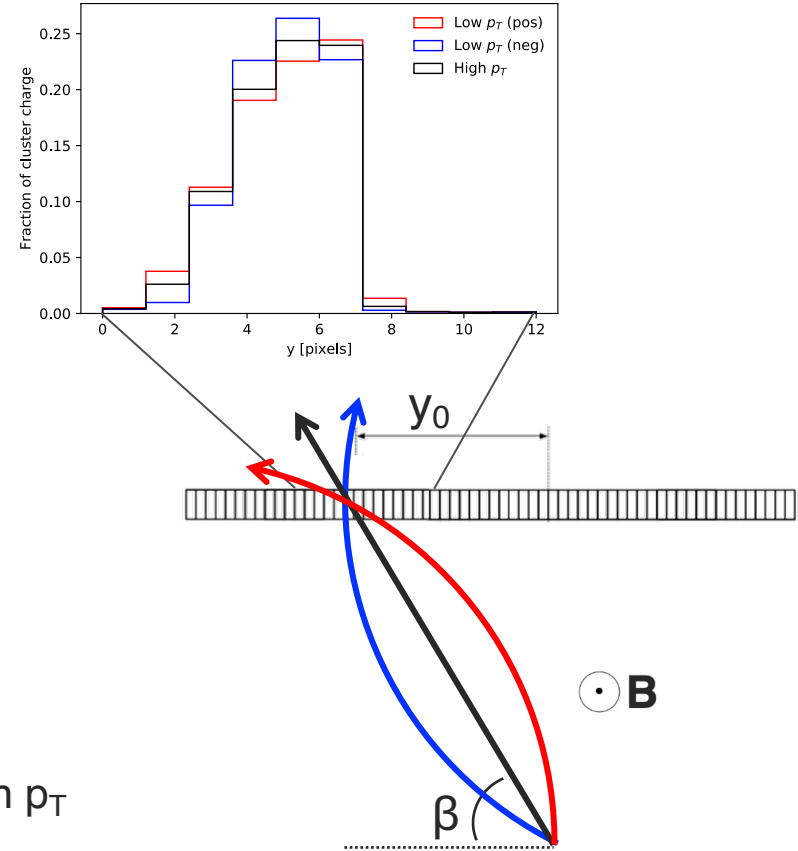
- Select and read out clusters created by particles with high transverse momentum (p_T)
- More than 95% of CMS pixel hits have $p_T < 2$ GeV

Potential for large reduction at HL-LHC



Classification based on particle p_T

- $p_T \sim$ radius of curvature, correlated with Magnetic field strength (B)
Position of the hit in the bending direction (y_0)
Angle in the bending plane of B (β)
Sign of the charge
- Train a classifier to select clusters with $p_T > 200$ MeV
Input data: cluster image projected onto y-axis
- Three classes:
Low p_T negative charge, **low p_T positive charge**, high p_T



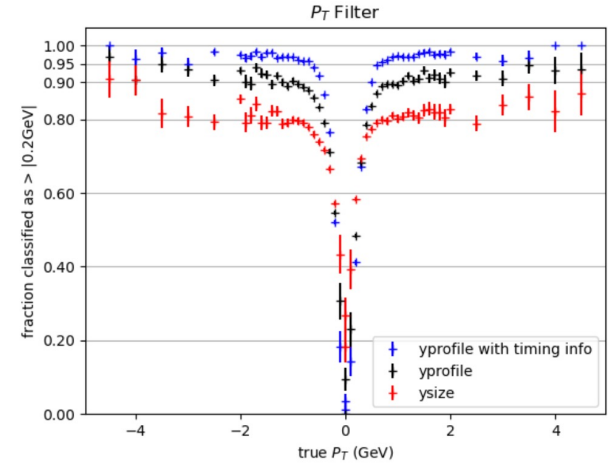
Performance of the DNN p_T filter

- Full precision network:

Projected cluster size only (1)

Projected cluster shape (2) (selected as baseline)

Timing information (3) promises 5-10% efficiency gain



How much do we discard? How much of what we keep is $p_T < 2 \text{ GeV}$? How much of what we discard is $p_T > 2 \text{ GeV}$?

Model	Data Reduction	False Positives	False Negatives
Model 1	77.9 %	13.4%	20.7 %
Model 2	65.8 %	10.9%	13.4 %
Model 3	57.4 %	8.9 %	8.1%


Model 4: Spiking neural network is a work in progress

Implementation in 28nm CMOS

- Network quantization

Input charge distribution binned for 2 bit ADC

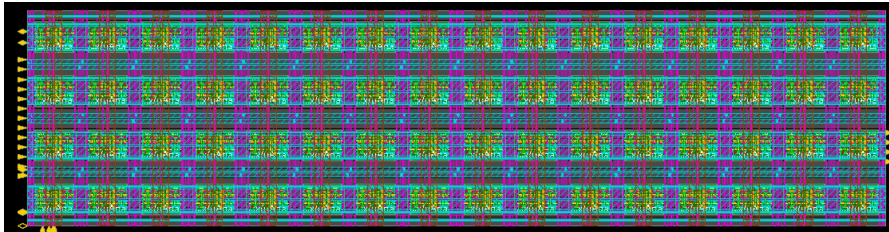
Quantization-aware training in Tensorflow/Keras

 translates model into hardware specification for high-level synthesis (HLS)

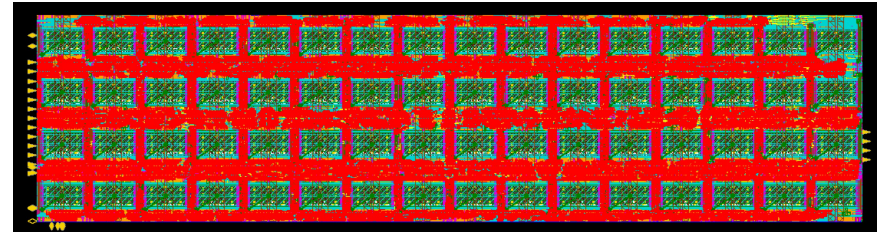
Siemens Catapult HLS to generate RTL implementation

- Fully reprogrammable NN weights

Floorplan with analog pixels with power and bias grid



Red = classifier algorithm



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

Data featurization on-ASIC

- Train an algorithm to extract properties of the incident particle

Read this out instead of raw data

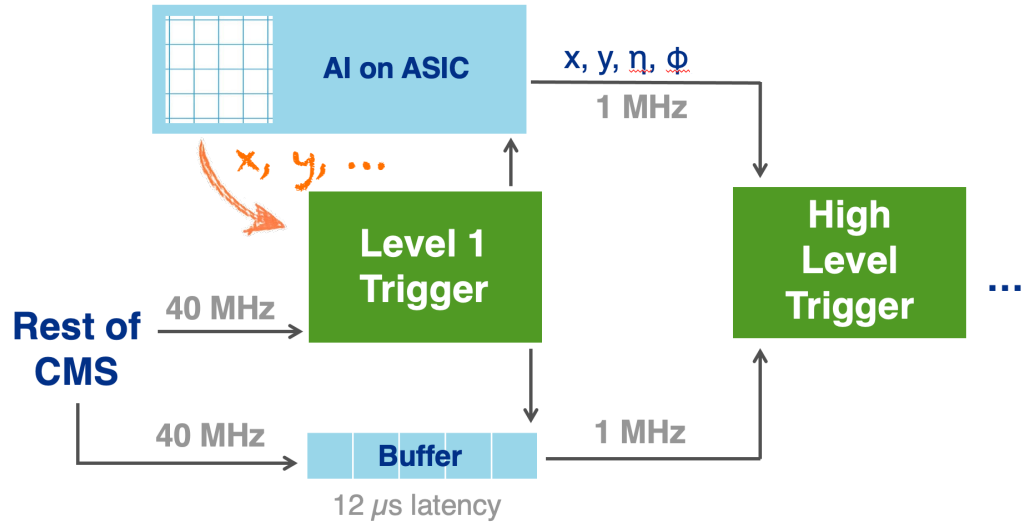
- A form of **compression**

Technically lossy, but fully preserves physics information

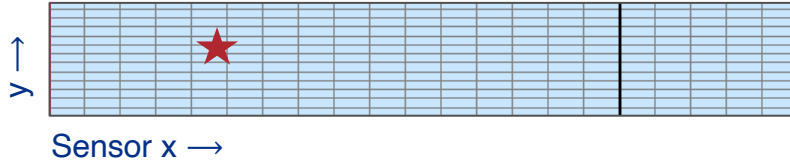
Size of readout depends on number of clusters, but not on cluster size

- Mixture density network gives us both central value and **meaningful uncertainty** on the measured quantity

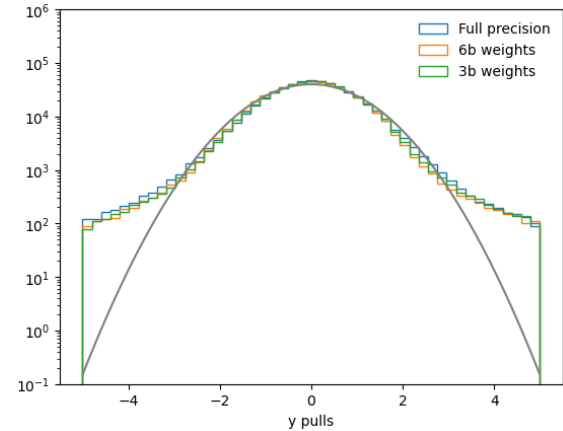
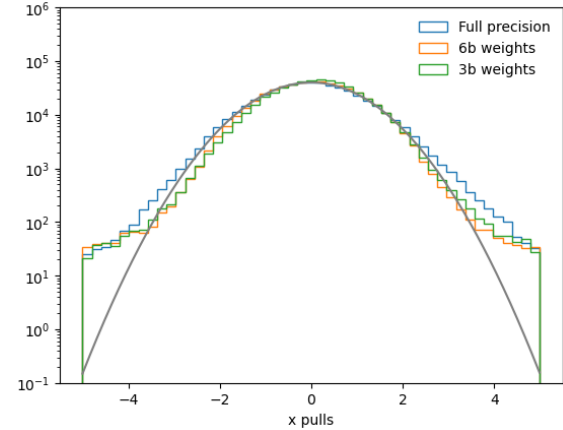
Predicts the parameters of a likelihood distribution



Predicting hit position & uncertainty

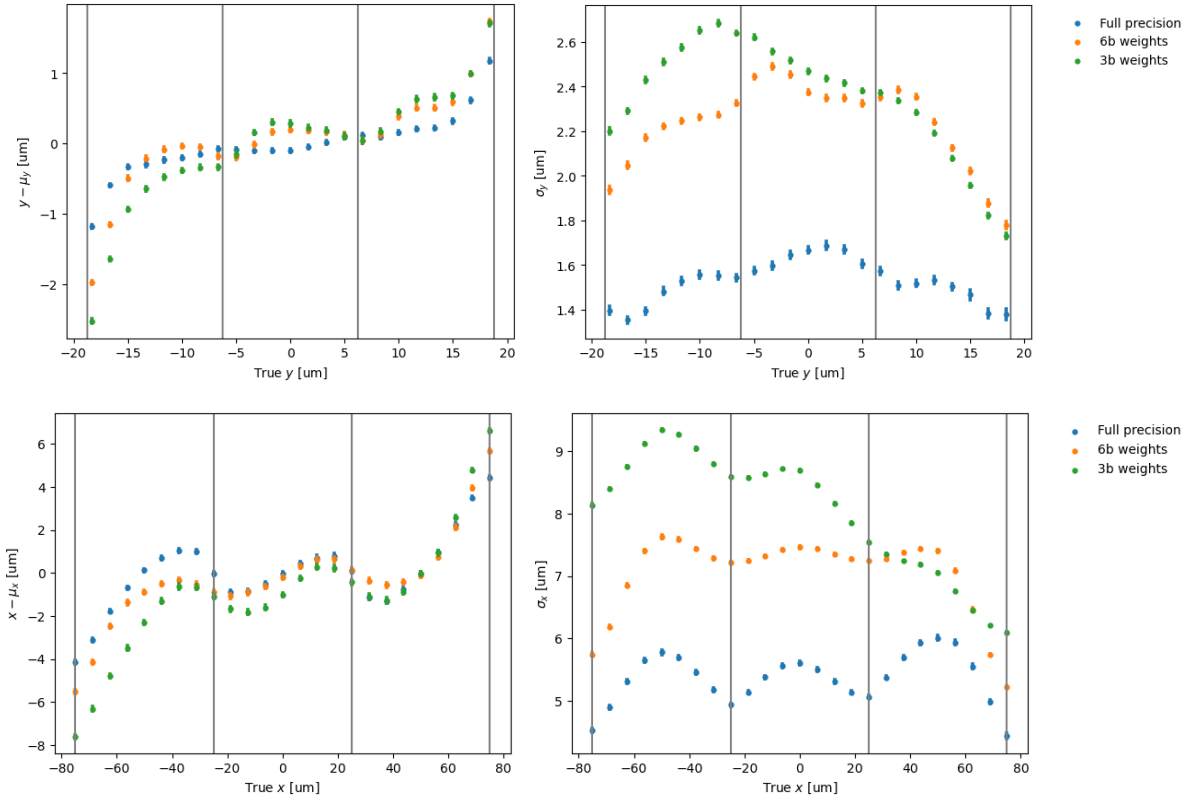


- Gaussian loss function (predict μ , σ)
- Simple networks very performant
 - Single layer NN, 10^6 training clusters
 - Quantization aware training with QKeras
- Training input = cluster shape projected onto relevant axis
 - Negligible correlation between x, y



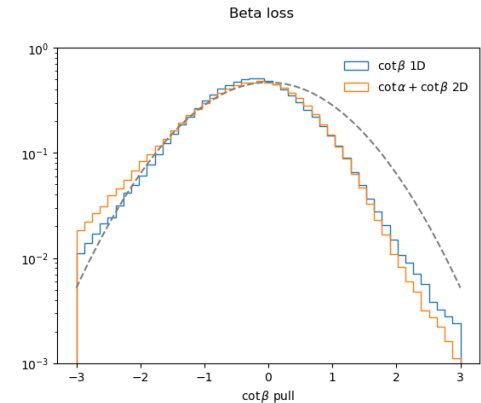
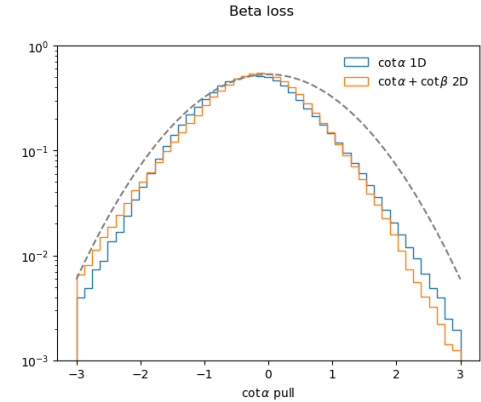
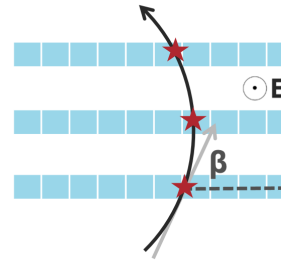
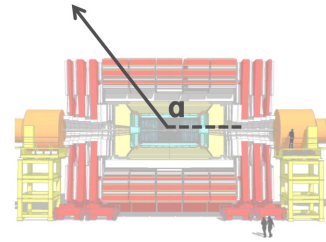
Predicting hit position & uncertainty

- Top row: y , bottom row: x
- Left column: residuals
- Right column: uncertainty
- Low precision weights \rightarrow larger uncertainty
- Models shown use cluster shape input only
- Addition of timing information improves performance



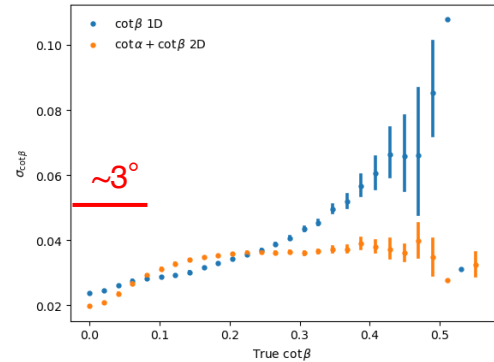
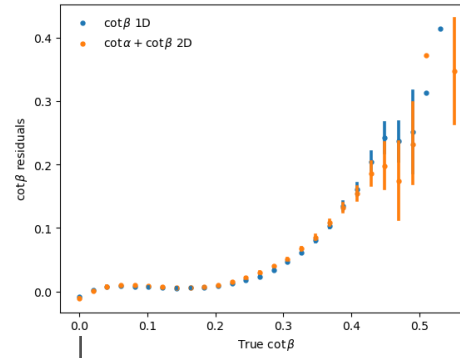
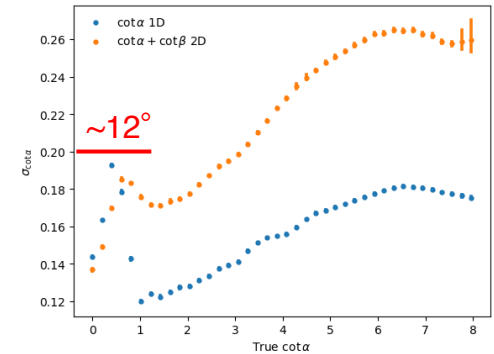
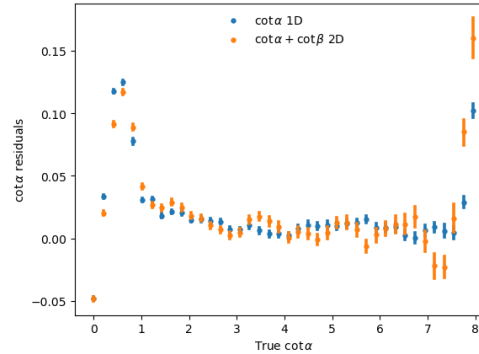
Predicting angles & uncertainty

- Beta distribution loss function (params a, b)
Mode and variance are functions of a, b
- More complex networks compared to x, y
3 NN layers, 10^6 training clusters
- Training input = cluster shape
Full 2D image (orange) and projected (blue)
Negligible correlation between α, β
- Predict absolute value of cotangent
Approximately linear in projected cluster size
Sign of the angle requires timing information



Predicting angles & uncertainty

- Single-pixel clusters impact prediction at low $\cot \alpha$
 - Pixel pitch is “large” in x
 - Best guess = center of the pixel \rightarrow some large residuals
- Dataset is only populated to $\pm 30^\circ$ from normal in β
 - Expect to reduce bias by expanding dataset
- Studies ongoing
 - Convolutional NN \rightarrow less area
 - Quantization to be explored



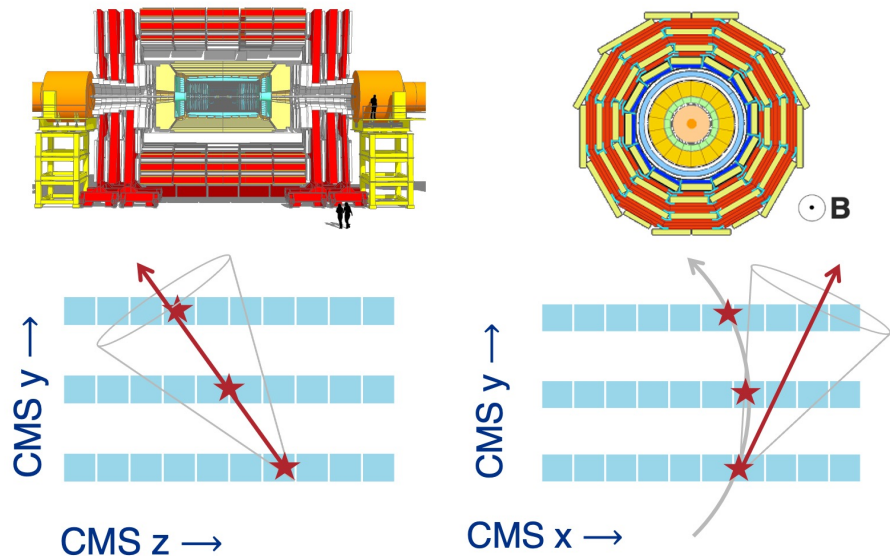
Normal incidence

Angles & their uncertainties

- More complex final states \rightarrow more hits \rightarrow more hit combinations for track seeding
Computationally very expensive and slow 😞

Angles & their uncertainties

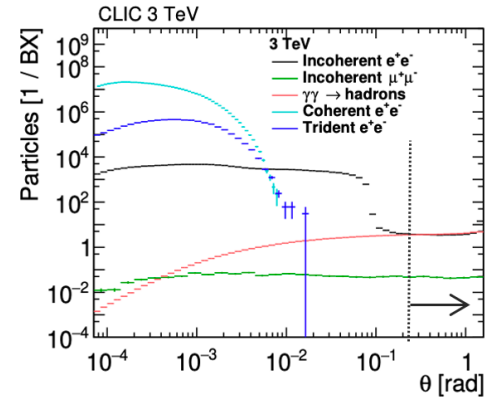
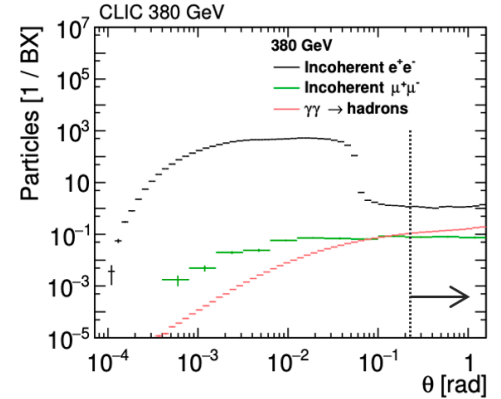
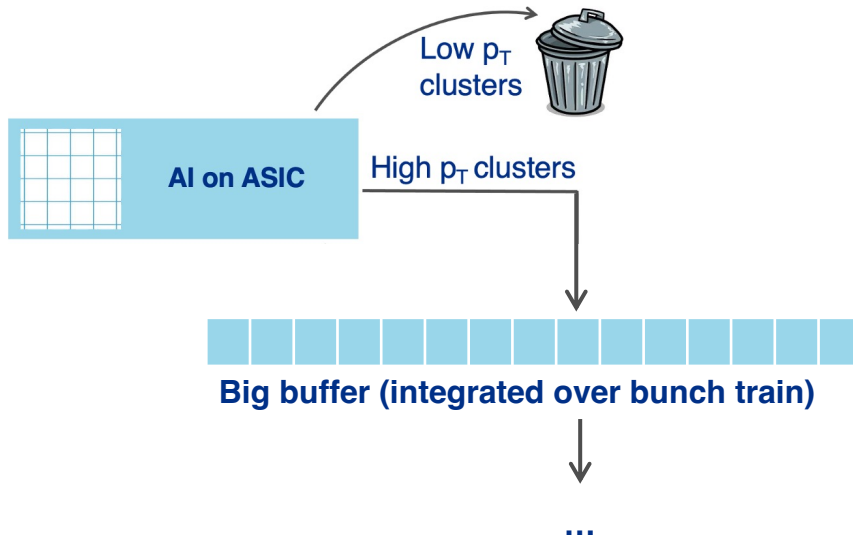
- More complex final states \rightarrow more hits \rightarrow more hit combinations for track seeding
Computationally very expensive and slow 😞
- Predicted angle + uncertainty gives a cone where you can expect a hit in the next layer, **reducing combinatorics**
Small uncertainty \rightarrow small cone
No timing \rightarrow $|\alpha|$, $|\beta|$ only \rightarrow 2 cones
- Fast tracking and vertexing
Very valuable for hh , $e+e^-$ and $\mu\mu$!
At HL-LHC: makes pixel trigger feasible?



e^+e^- collisions: on-ASIC filtering

- Reject hits from beam backgrounds corresponding to spiraling e^+e^- from e.g. incoherent pair production

Train a classifier to remove hits from tracks with low p_T , small θ



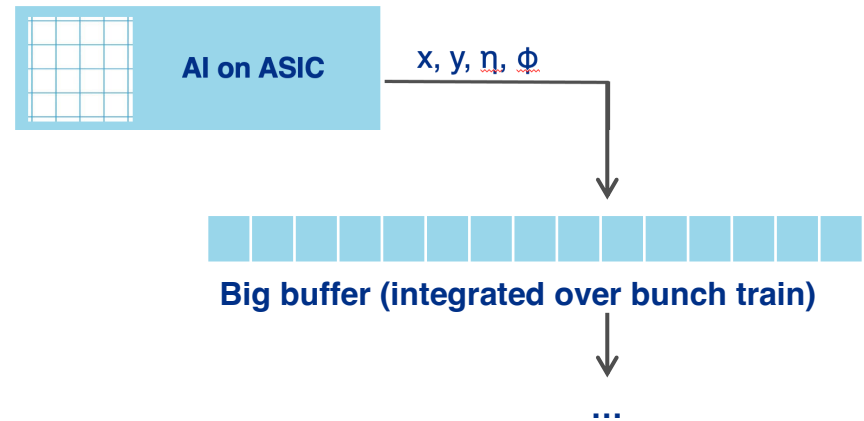
e^+e^- collisions: on-ASIC featurization

- Read out incident particle properties and uncertainties instead of pixel array
- Size of stored pixel data is **independent of geometry**
Decouples buffer size from choice of pixel pitch, sensor thickness
- Good use case for **MAPS with 3D integration**

MAPS → small pixels, thin sensors

MAPS shift information to the periphery

Additional layer on top would provide area to do the NN regression



e^+e^- collisions with on-ASIC data reduction

- **Critical design constraints** to keep beam backgrounds out of acceptance could be **relaxed**

Innermost radius of vertex detector (right), θ acceptance, pixel pitch

- **Reprogramming NN weights for different \sqrt{s}** ensures the most effective filtering

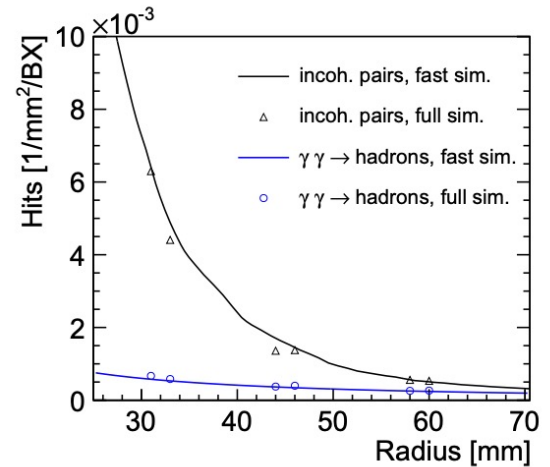
Adjust NN weights to change p_T and θ thresholds or compensate for radiation damage effects

- Possibility to **reduce thermal load** (material budget) by reading out less data

Spiking neural networks are especially energy-efficient

- Can significantly **increase the rate**

Could consider a low-energy machine that might require a trigger



Smart pixels: summary

- AI on-chip has great potential to **reduce data rates to manageable levels**

First implementation of the p_T filtering looks very promising!

Feature extraction for x , y , α , β underway

- Plan to leverage **emerging technologies** to improve energy efficiency, accuracy
- Co-design with focus on preserving **information that is useful for physics**

For e^+e^- this reaches all the way down to accelerator level

Smart pixels would provide **more flexibility** in experimental design at linear e^+e^- machines

The smart pixels team

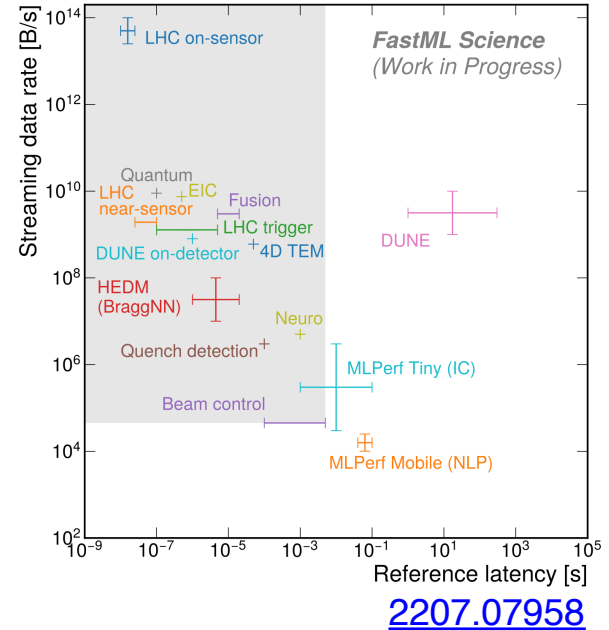
Alice Bean, Doug Berry, Manuel Blanco Valentin, Jennet Dickinson, Giuseppe Di Guglielmo, Karri DiPetrillo, Farah Fahim, Lindsey Gray, Jim Hirschauer, Shruti R. Kulkarni, Ron Lipton, Petar Maksimovic, Corrinne Mills, Benjamin Parpillon, Gauri Pradhan, Morris Swartz, Nhan Tran, Jieun Yoo, Aaron Young



Backup material

Pixel detectors at the LHC

- Highest data rates in HEP!
 - Only read out for triggered events
 - Measure charged particle tracks and vertices
- And getting higher...
 - Next generation detectors promise better resolution (position & angle), precision timing
 - More information, but also more data

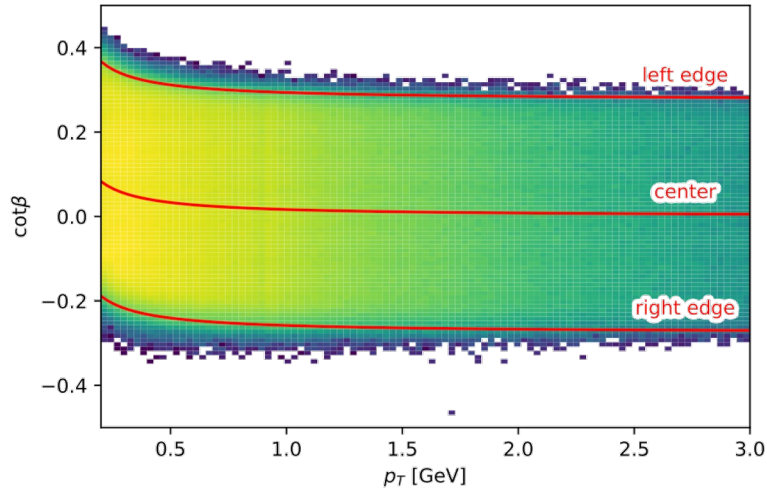


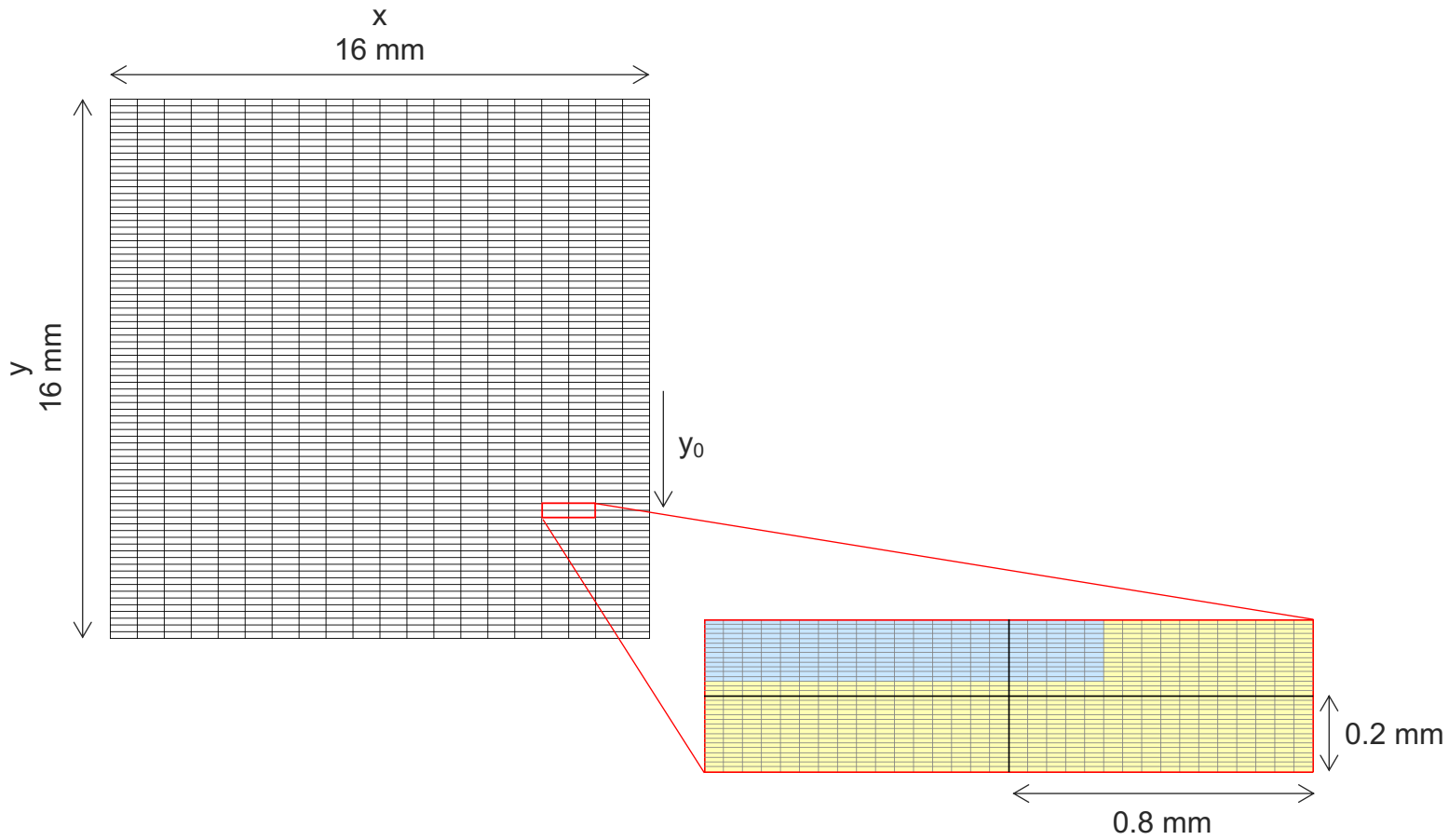
What would we gain if we could analyze it all? Some aspirational targets:

- **Higgs self-coupling** : 5x increase in the low- m_{hh} spectrum from b-jet triggers.
- **WIMP dark matter** : 50x rate for low- p_T / disappearing tracks / long-lived particles.
- **New capabilities for high-rate, soft objects** : e.g. dark sector BSM, B-physics, and more!

Incident angle, p_T , and y_0

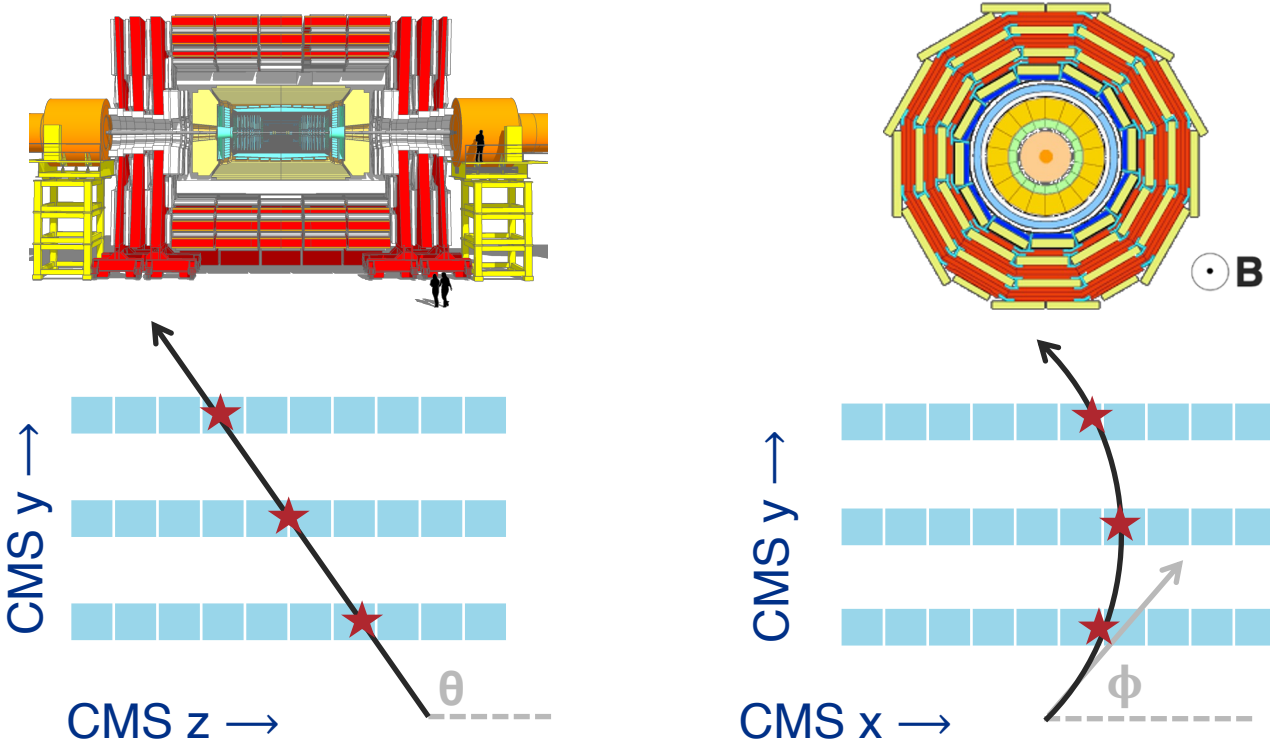
- Positive charge only



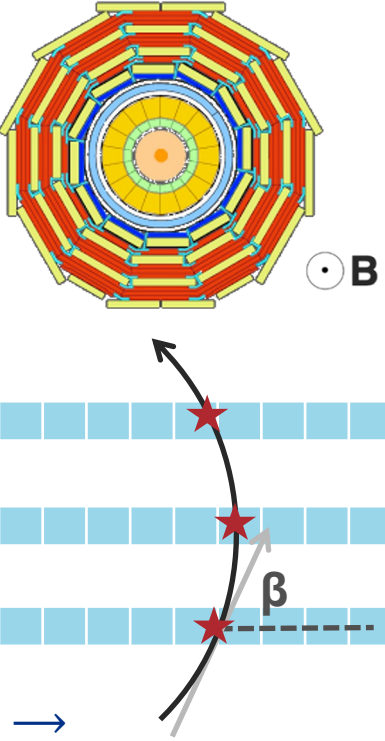
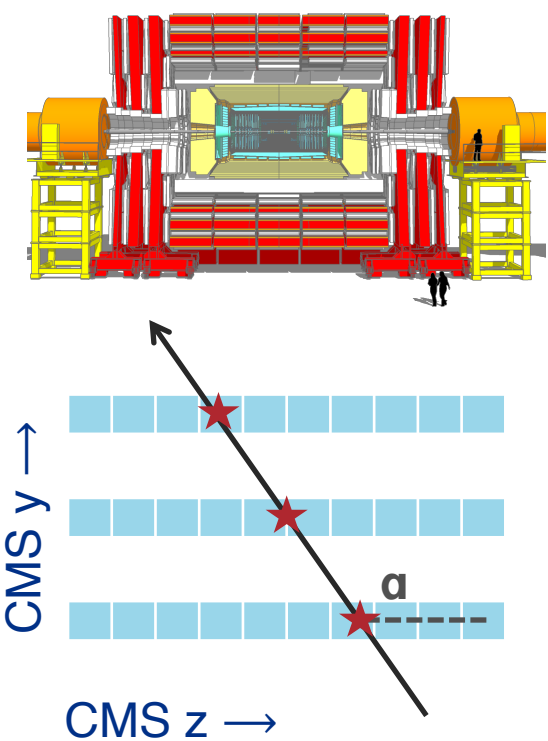


Track diagrams

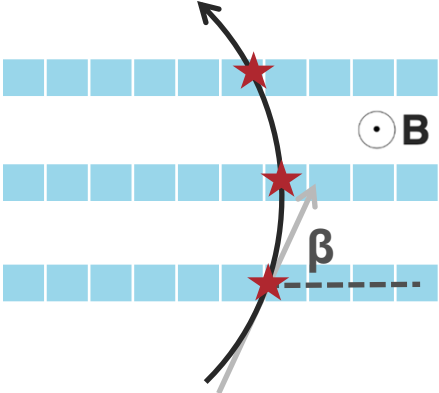
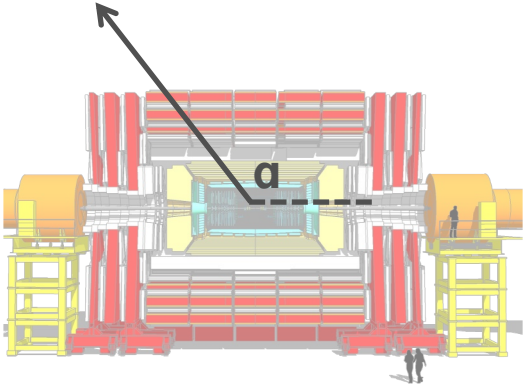
- Combined with other sensor layers for 3D tracking



Track diagrams: angles



Track diagrams: angles



Track diagrams: angles (2)

