Neural Network-Based Primary Vertex Reconstruction with FPGAs for the Upgrade of the CMS Level-1 Trigger System

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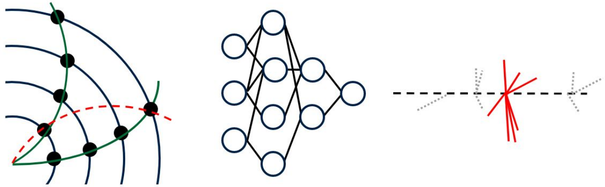
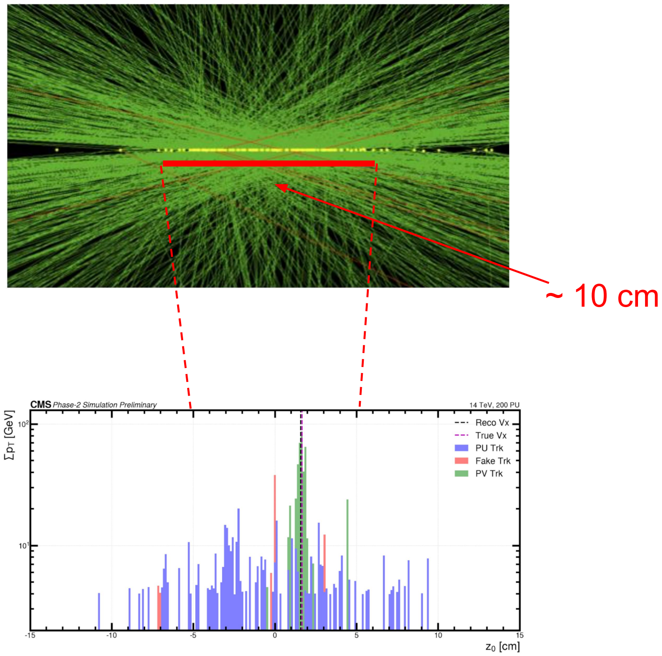


Introduction

- HL-LHC, increased number of simultaneous proton-proton interactions per bunch crossing. Good for rare physics searches, bad for current era triggering
- Tracks for the first time at L1 trigger
- Tracks to locate primary vertex (the proton-proton collision with the highest $\sum p_T^2$)
- Associate tracks and other trigger objects to vertex, reducing impact of pileup on downstream algorithms (e.g. PUPPI) -> maintain sensitivity

High pile up HL-LHC

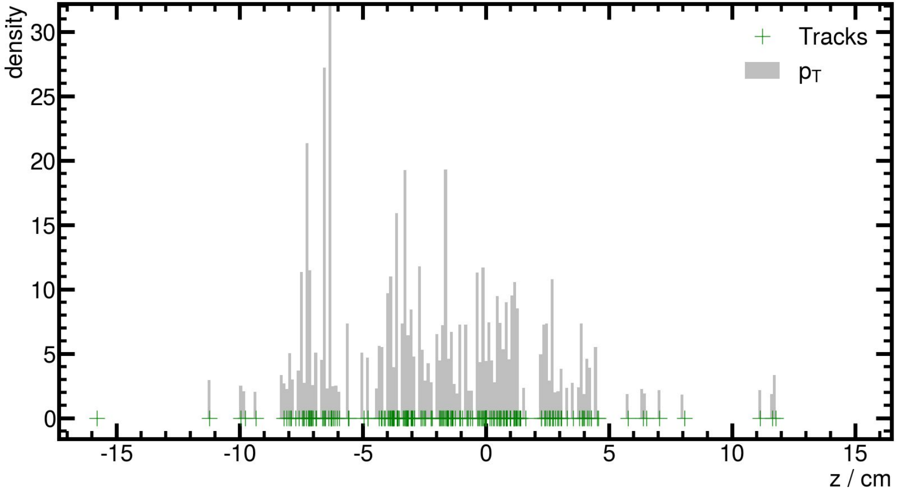


Finding primary vertex essential for reducing impact of pile up on L1 triggering

Baseline Vertex Finding Chain

Track Finding

Produces tracks > 2 GeV,
~100s per event with PU200



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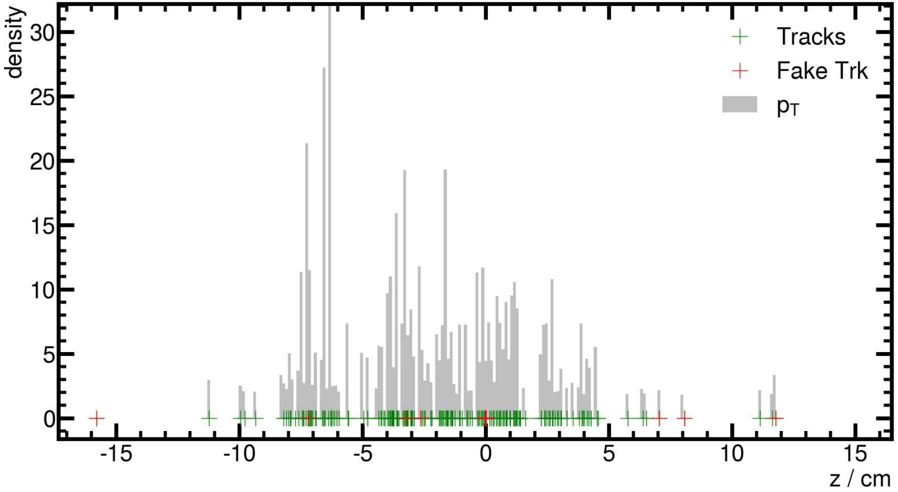
Based on χ^2 parameters from track finding, simple cuts



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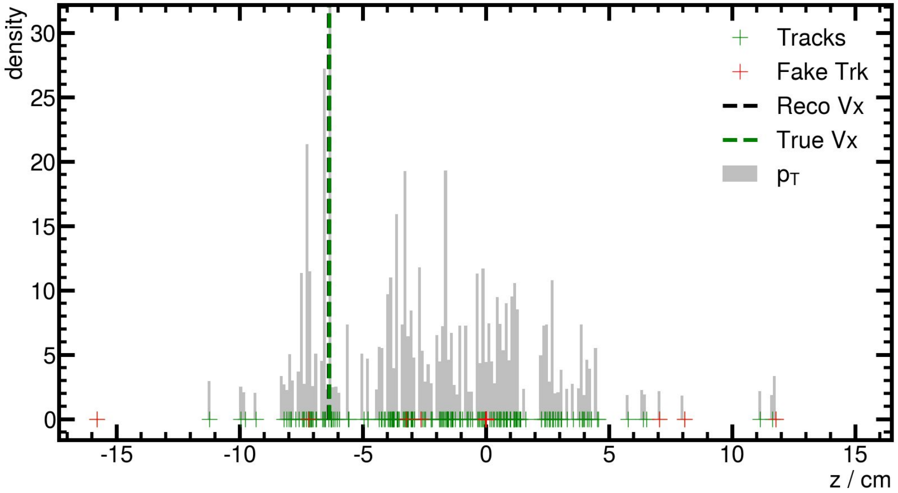

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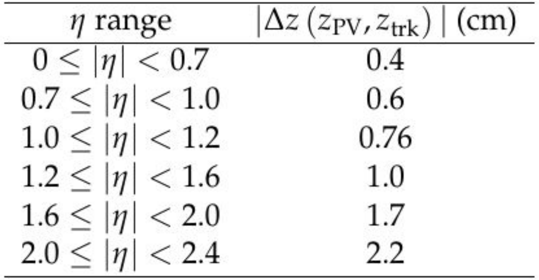
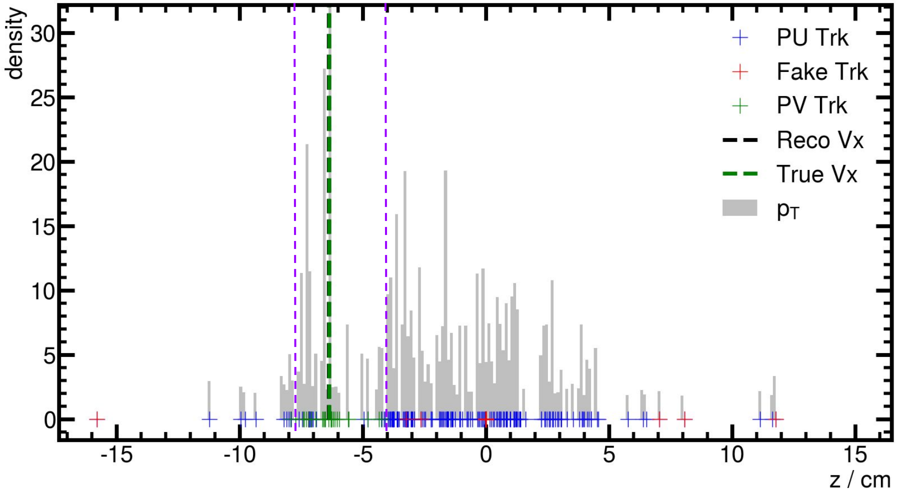
Track to Vertex Association

Fixed window in z_0 or multiple windows based on track η



η range	$\lvert\Delta z\,(z_{\mathrm{PV}}, z_{\mathrm{trk}})\rvert$ (cm)
$0 \leq \lvert\eta\rvert < 0.7$	0.4
$0.7 \leq \lvert\eta\rvert < 1.0$	0.6
$1.0 \leq \lvert\eta\rvert < 1.2$	0.76
$1.2 \leq \lvert\eta\rvert < 1.6$	1.0
$1.6 \leq \lvert\eta\rvert < 2.0$	1.7
$2.0 \leq \lvert\eta\rvert < 2.4$	2.2



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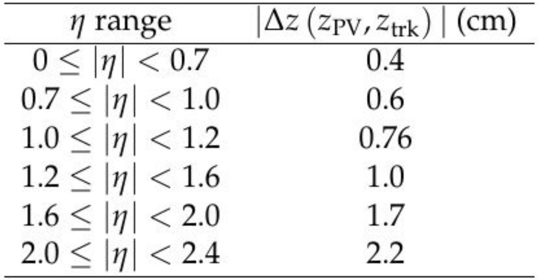
Track E^T_{Miss} PF/PUPPI etc.	Downstream Algorithms



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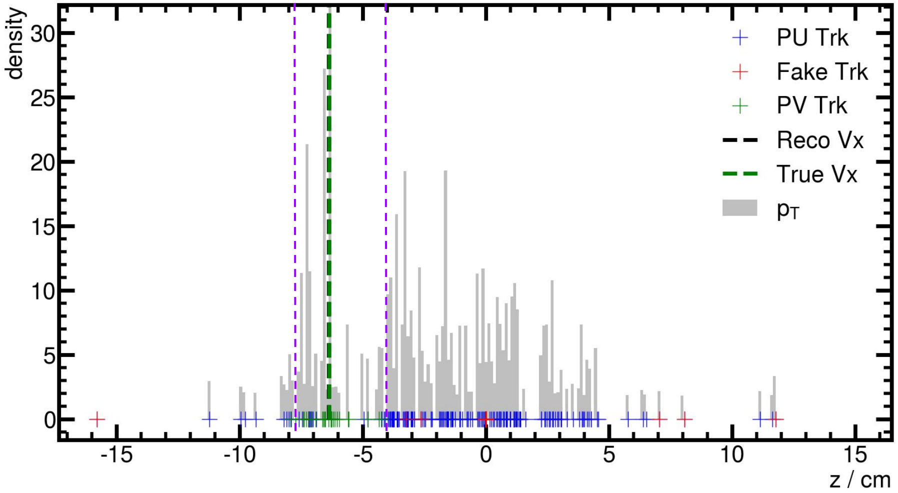
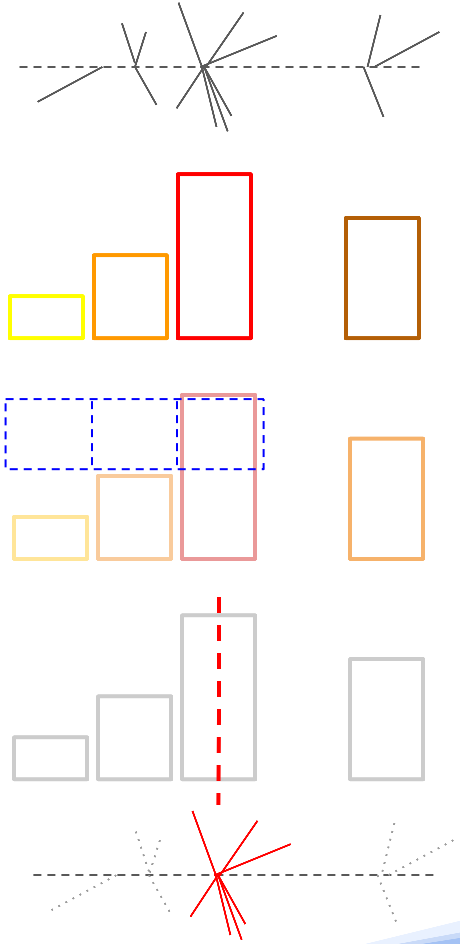


Vertex Finding Concept



Baseline

p_T Weighting

Weighted Histogram

3-Bin Convolution

Argmax

Cut-Based

Vertex Finding Concept

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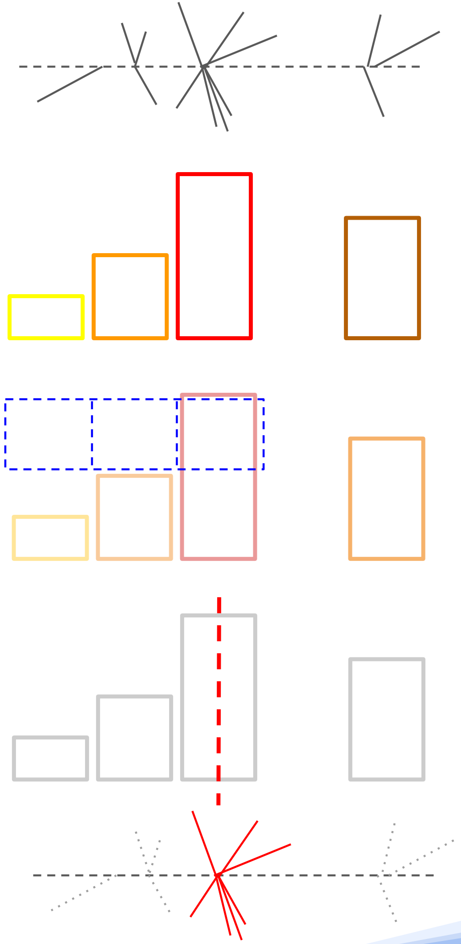

End to End Neural Network

DNN multiple track features

Vertex Finding Concept

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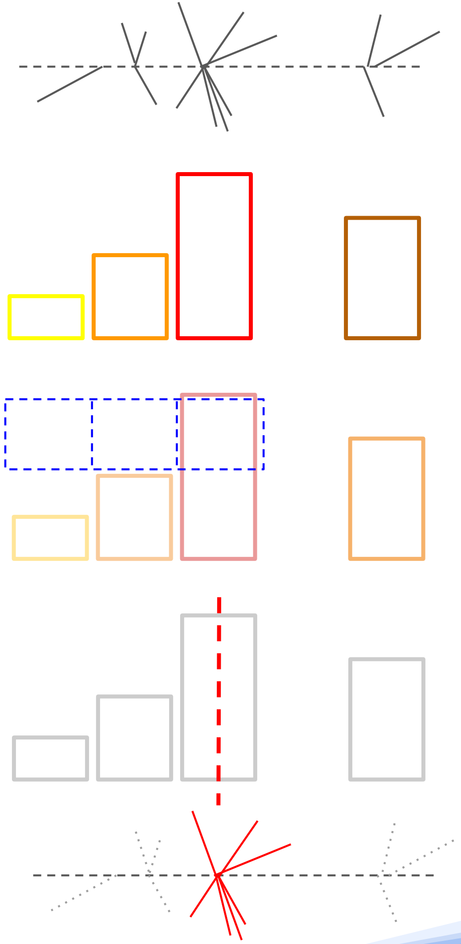

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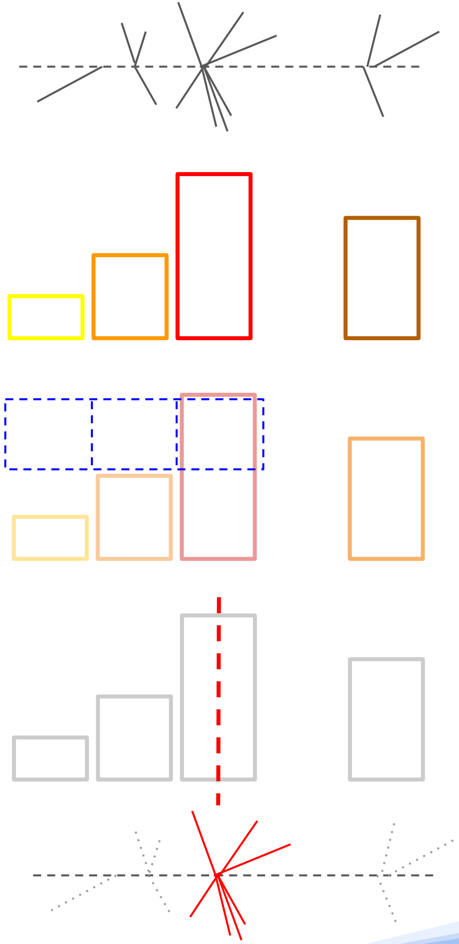

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Multilayered CNN

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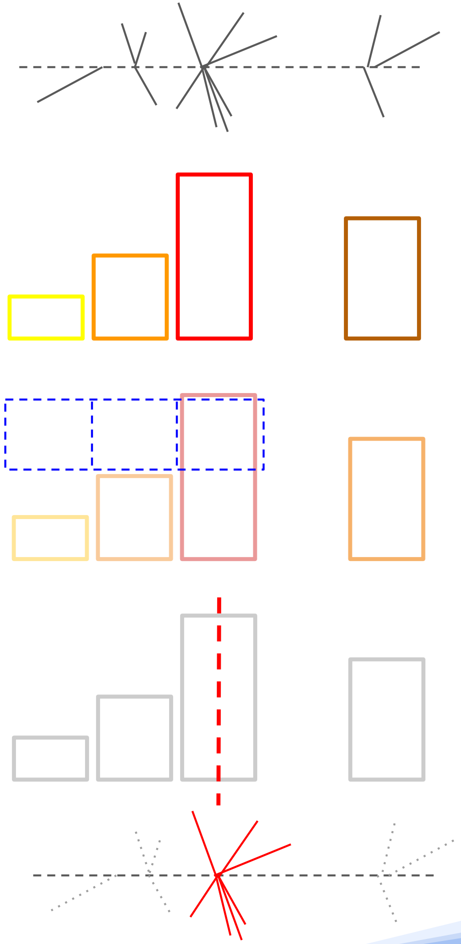

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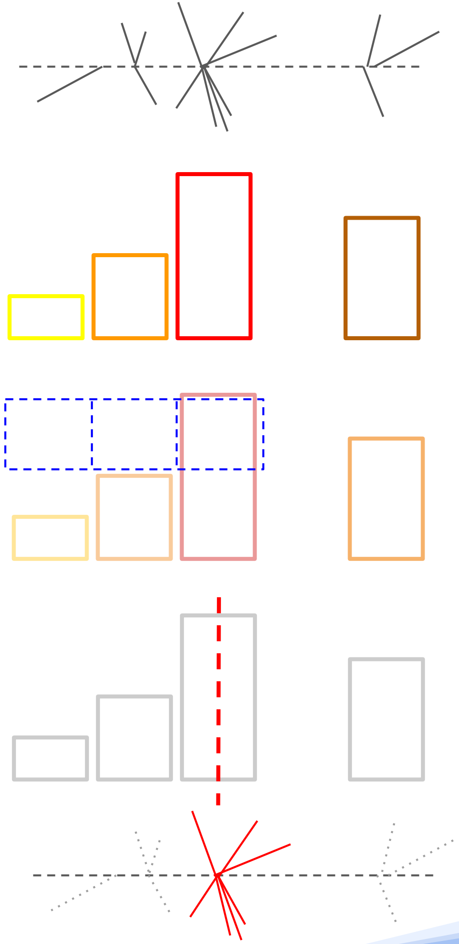

End to End Neural Network

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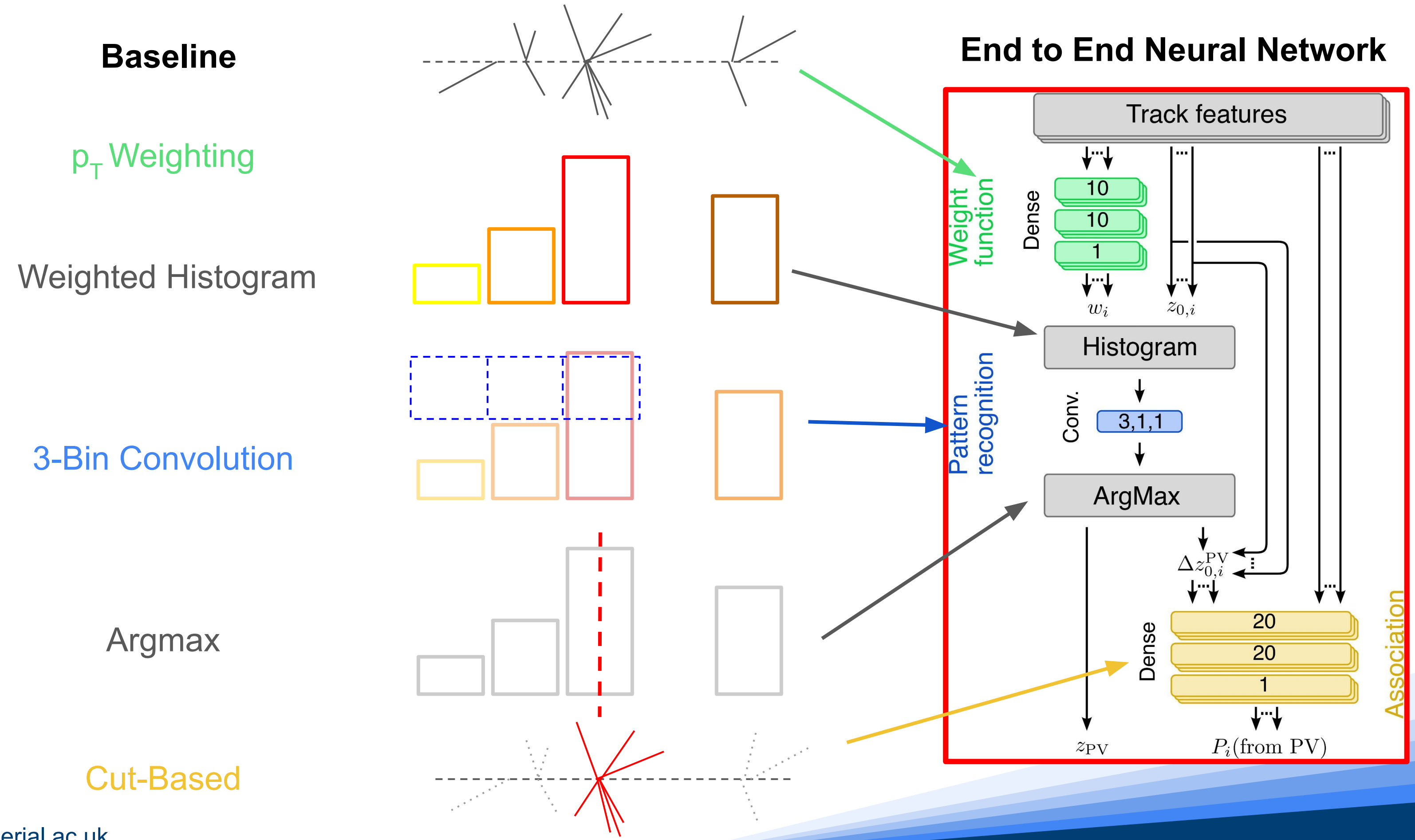
DNN with z_0 distance, track features and latent features

Vertex Finding Concept



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End to End Neural Network

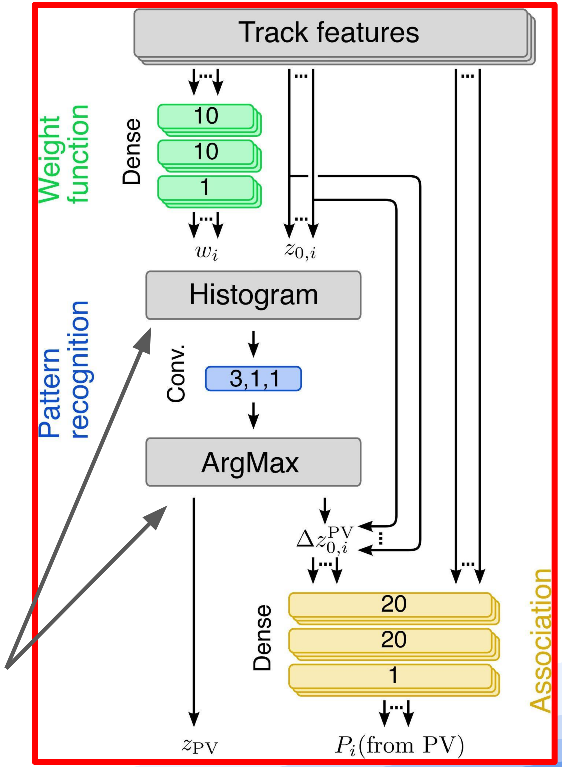
End to End Neural Networks for Vertex Finding

○ Network trained with 2 part loss function -> Event level PV regression, track level PV track classification

○ Simultaneous knowledge of both PV position and track to vertex association

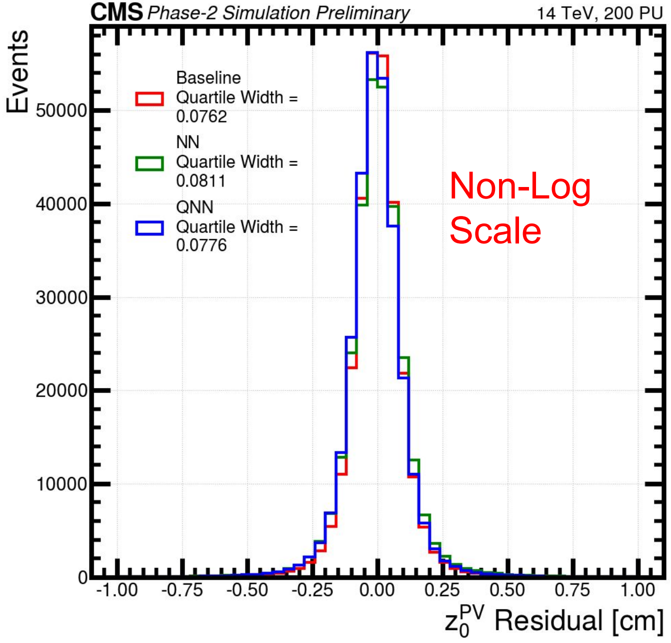
○ Robust to changes in track finding

○ Additional vertex quality

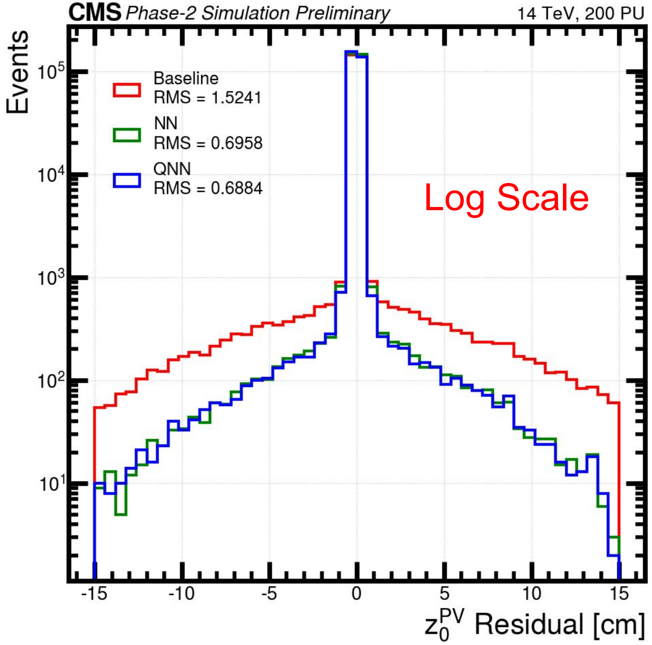


Differentiable

Performance - Vertex Regression



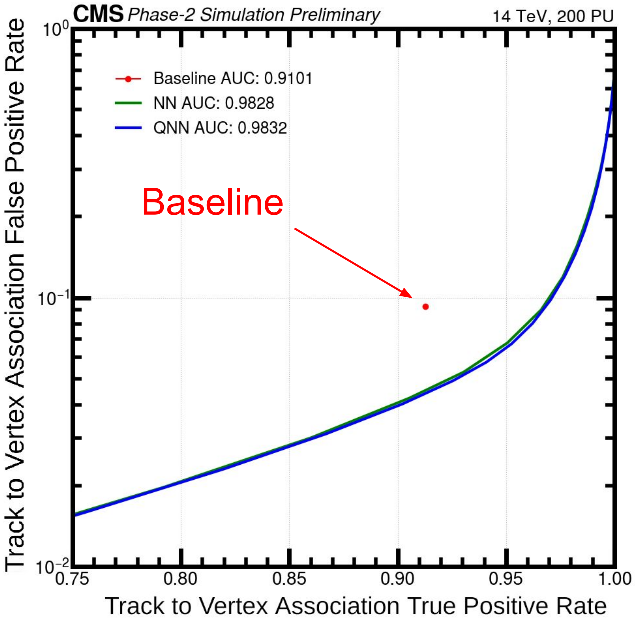
Non-Log Scale

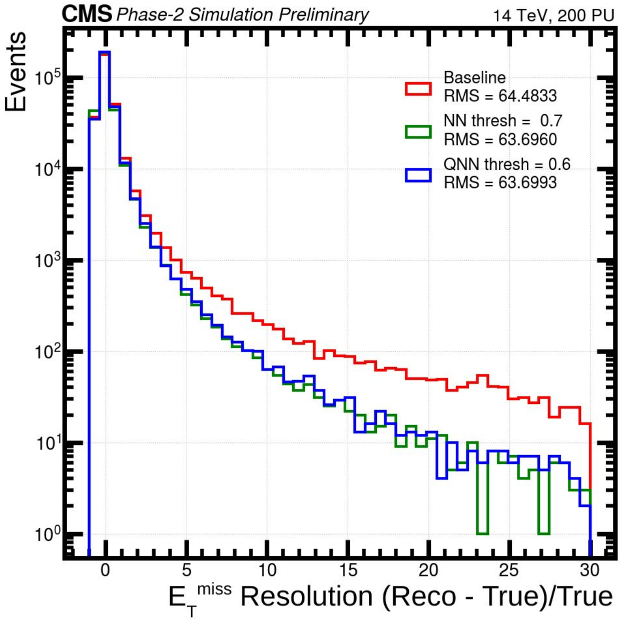


Log Scale

- Similar performance in core of residual
- 55% reduction in tails of residual
- Better identification of pileup vertices removing high p_T clusters
- Similar performance with compressed networks

Performance - Track to Vertex Association





- Improvement in E_T^{miss} calculation, reduction in tails of residual
- Returns likelihood of track belonging to vertex -> flexible threshold for downstream algorithms

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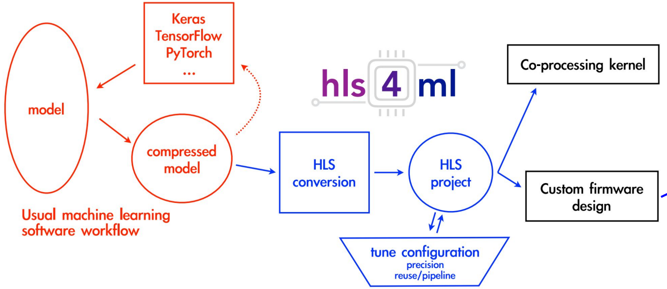
Firmware - Network Compression

Split Model
into 3 parts ->
Weight
Pattern
Association



Wire up generated HDL
within existing VHDL
GTT

Quantisation:
Restrict Bitwidths
Reduce DSP usage

Pruning:
Iteratively Remove Weights
L1 Regularization

VU9P	Latency (ns)	Initiation Interval (ns)	LUTs %	DSPs %	BRAMs %	FFs %
NN Weight	28	2.0	0.17	1.89	0.00	0.08
QPNN Weight	**14**	**2.0**	**0.04**	**0.00**	**0.00**	**0.02**
NN Pattern	42	38	2.54	3.74	5.28	3.20
QPNN Pattern	**30**	**26**	**2.12**	**0.00**	**5.28**	**2.96**
NN Assoc.	30	2.0	0.60	6.04	0.00	0.28
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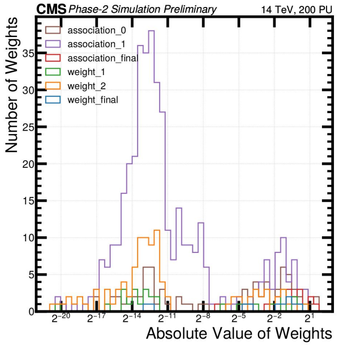
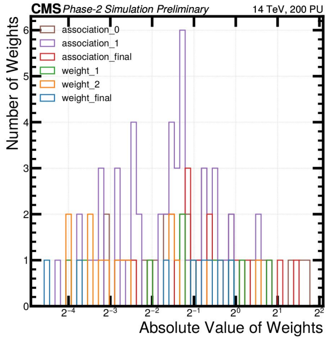


8 training cycles



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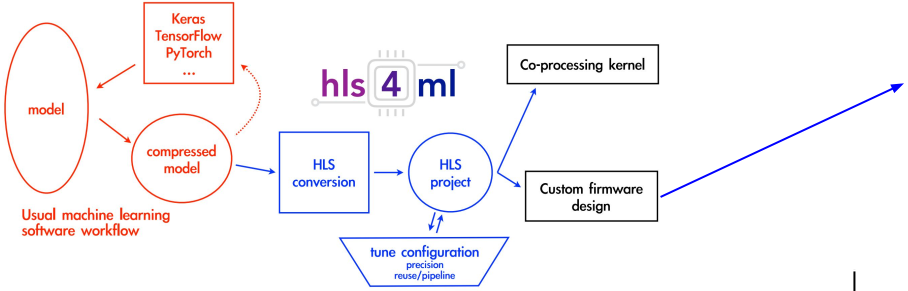

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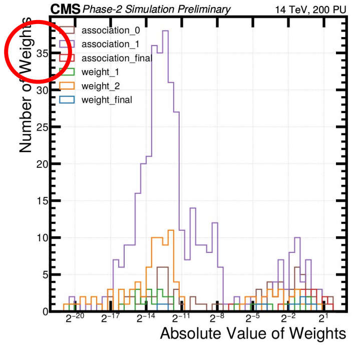

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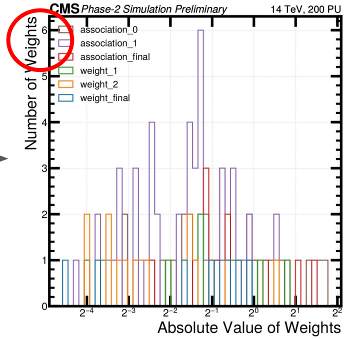

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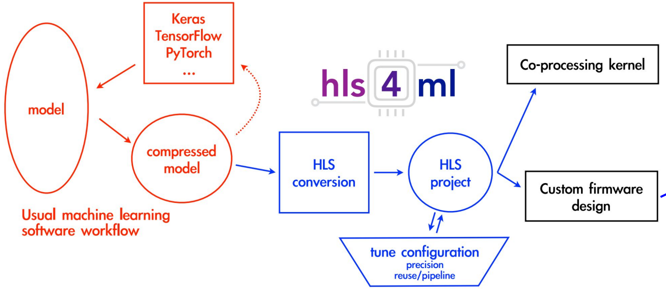

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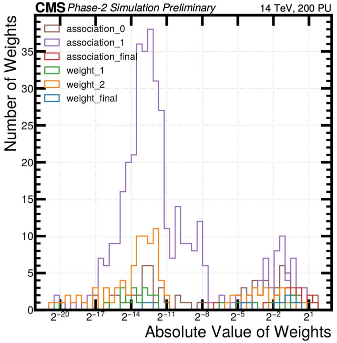

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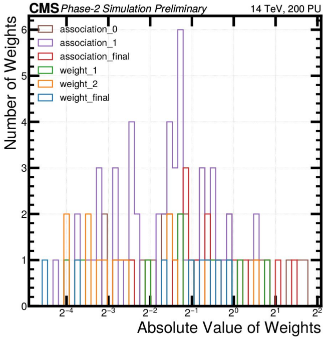

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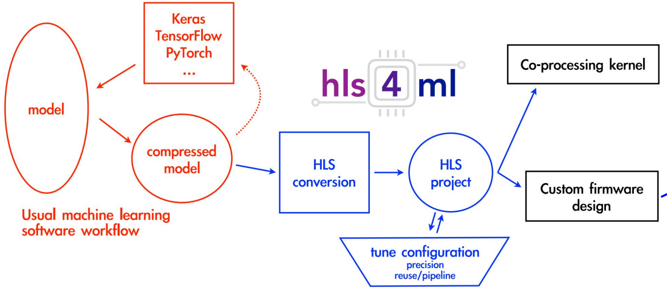

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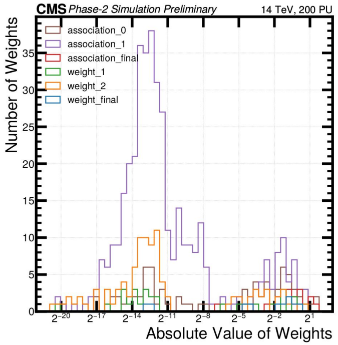

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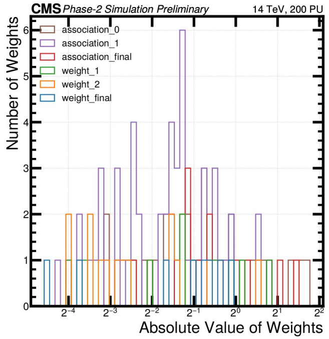

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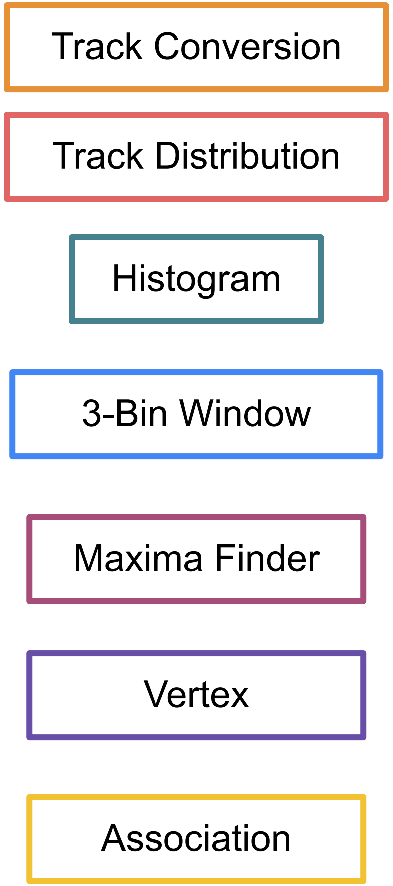
Implementation

- Take VHDL processing blocks of baseline histogramming approach
- VHDL **top entities** controlling input output signals of networks
- Targeted ⅓ **VU9P** running at **360 MHz**
- Meets timing after running networks through Vitis with better pipelining
- **108 ns** total algorithm latency



Track Conversion

Track Distribution

Histogram

3-Bin Window

Maxima Finder

Vertex

Association

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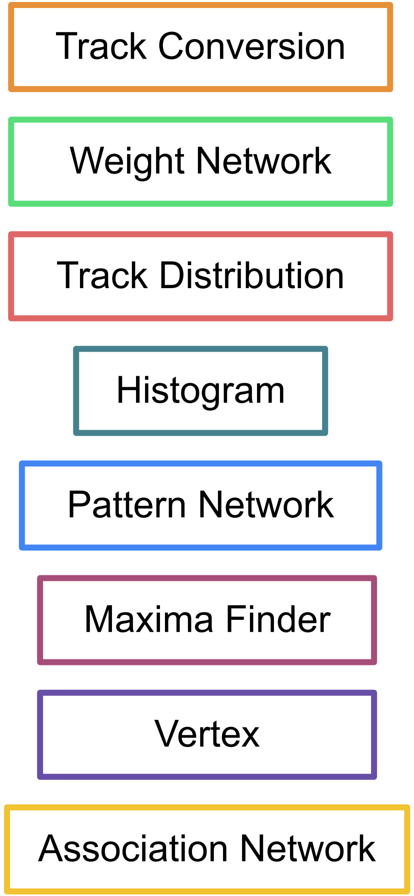

Track Conversion

Weight Network

Track Distribution

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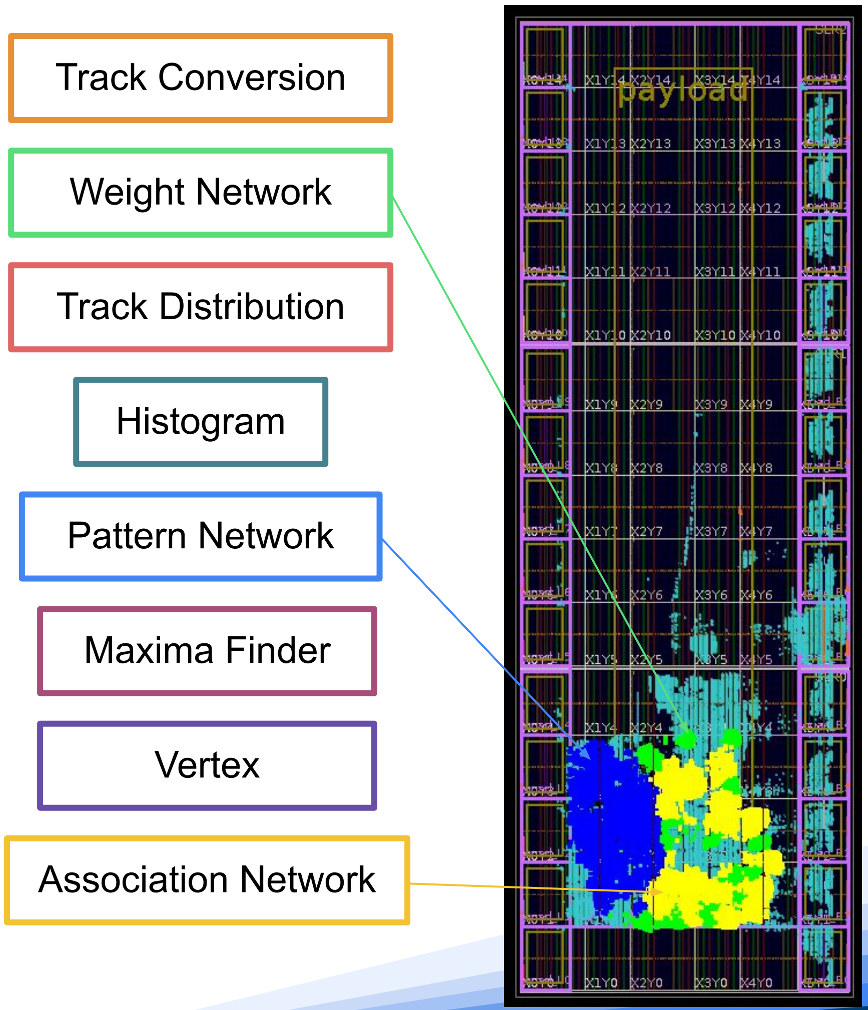

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Conclusion

Baseline Approach to Vertex Finding

End to End Neural Network for Vertex Finding

- Concept
- Performance

Firmware and Network Compression

Implementation

CMS Conference Note

Future Steps

Verify in Hardware

Downstream Physics Impact

Vertex Quality Estimation

Backup

Learning Track Weights

- Network learns ideal track weighting into histogram
- Histogram part of Network training cycle filled with:

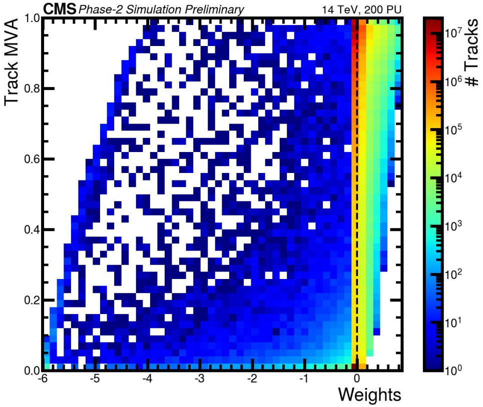
$$h_i = \sum_{j}^{\text{tracks}} \delta(j \in \text{bin } i) \times \boxed{w(p_{\mathrm{T},j}, \eta_j, \chi^2_j, \ldots)}$$

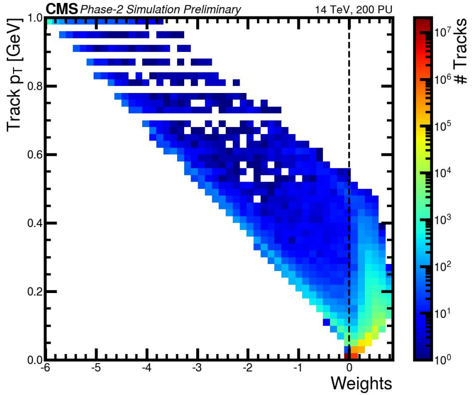
- Differentiated to give:

$$\frac{\partial h_i}{\partial \vec{w}} = \sum_{j}^{\text{tracks}} \delta(j \in \text{bin } i) \qquad \frac{\partial h_i}{\partial \vec{z}_0} = 0$$

- Passed through convolutional network and differentiable ArgMax to give peak

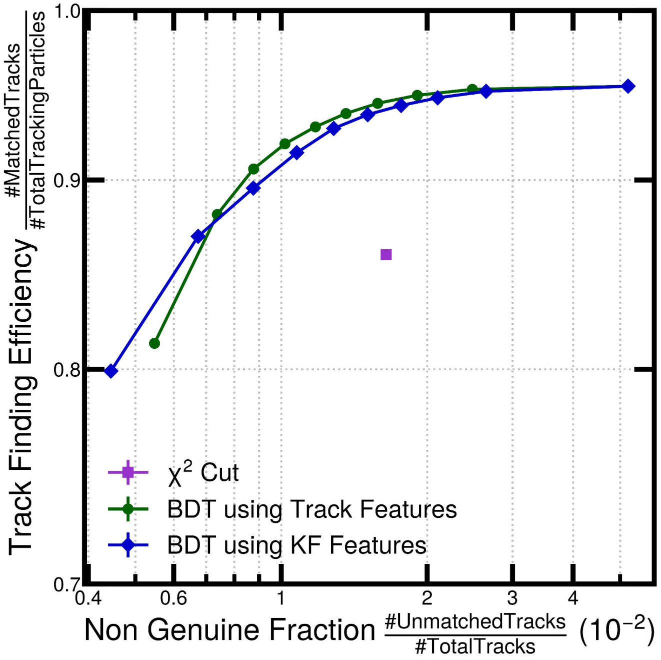
$$\sum_{i=0}^{N} i \frac{e^{x_i/T}}{\sum_{j=0}^{N} e^{x_j/T}}$$





Track Quality

- Fake rate is high ~20% at high p_T can use χ^2 cuts to reduce but big drop to tracking efficiency
- Use small BDTs to learn to classify fakes based on track fit and helix parameters
- Outperforms χ^2 cuts, high fake rejection with only small reduction to tracking efficiency
- Used as input feature to end-to-end neural network



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