

RICH pattern recognition with FPGA: from NA62 to dRICH

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The NA62 Experiment at CERN SPS

- Measurement of the K^+ decay:

$$BR(K^+ \rightarrow \pi^+ \nu \bar{\nu})$$

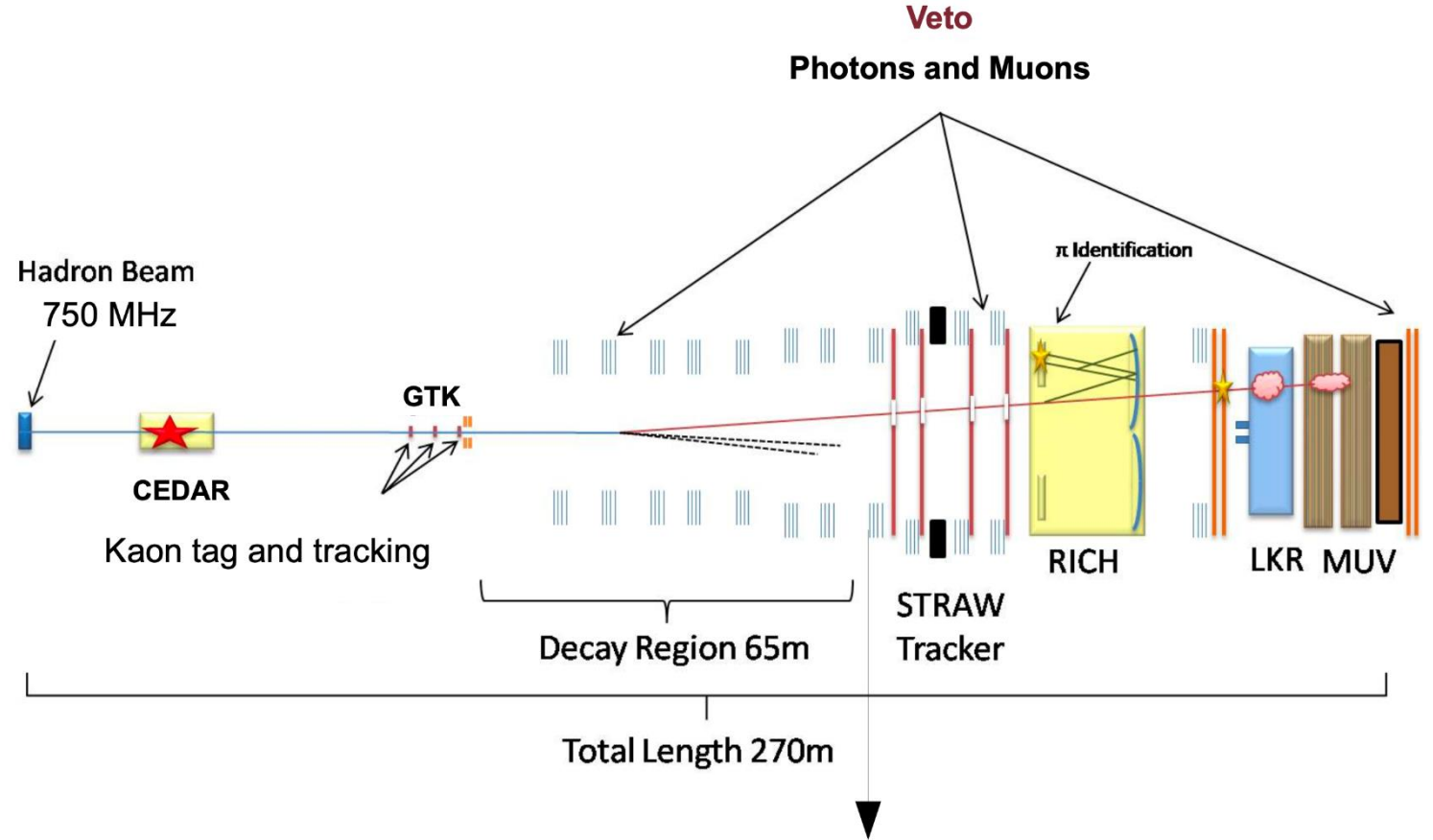
- **Ultra-rare channel, SM prediction:**

$$BR_{SM} = (8.60 \pm 0.42) \times 10^{-11}$$

Run I NA62 measurement:

$$BR_{NA62} = (10.6^{+4.0}_{-3.4}|_{stat} \pm 0.9_{syst}) \times 10^{-11}$$

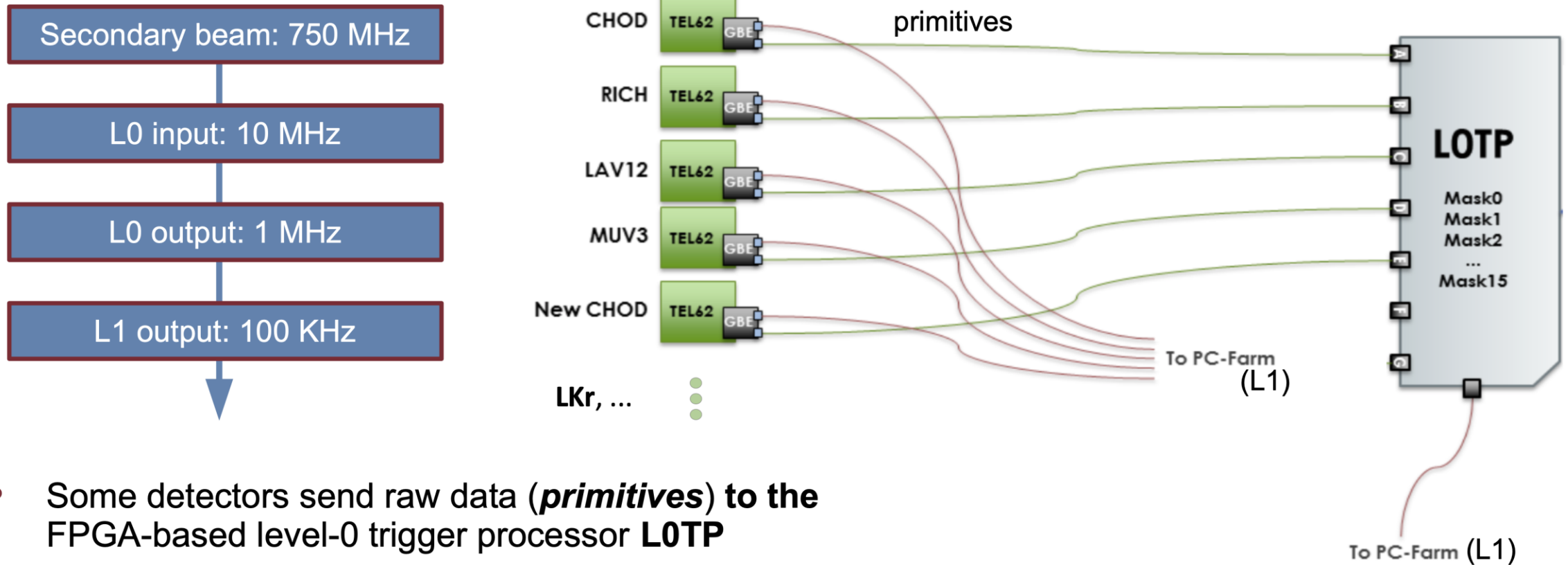
- **Fixed Target experiment:**
75 GeV secondary hadron beam
(6% kaons).



10 MHz event rate

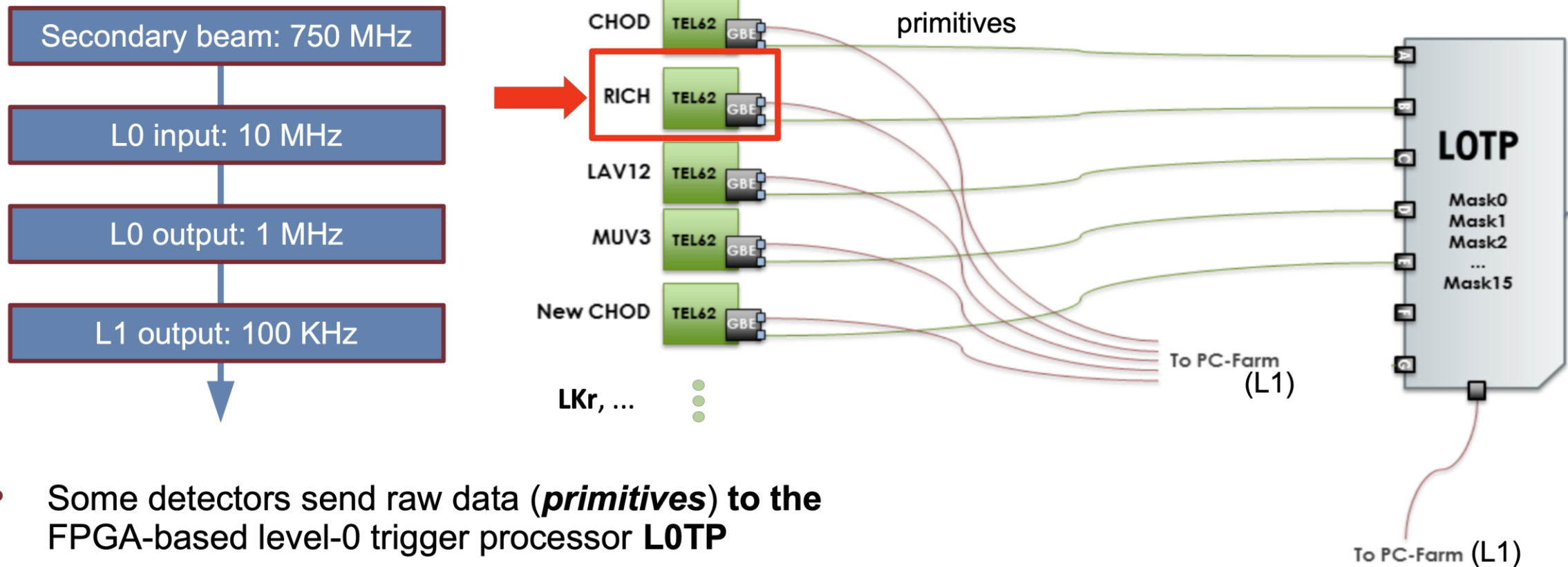
Need highly selective filtering system

The NA62 Data Acquisition and Low Level Trigger



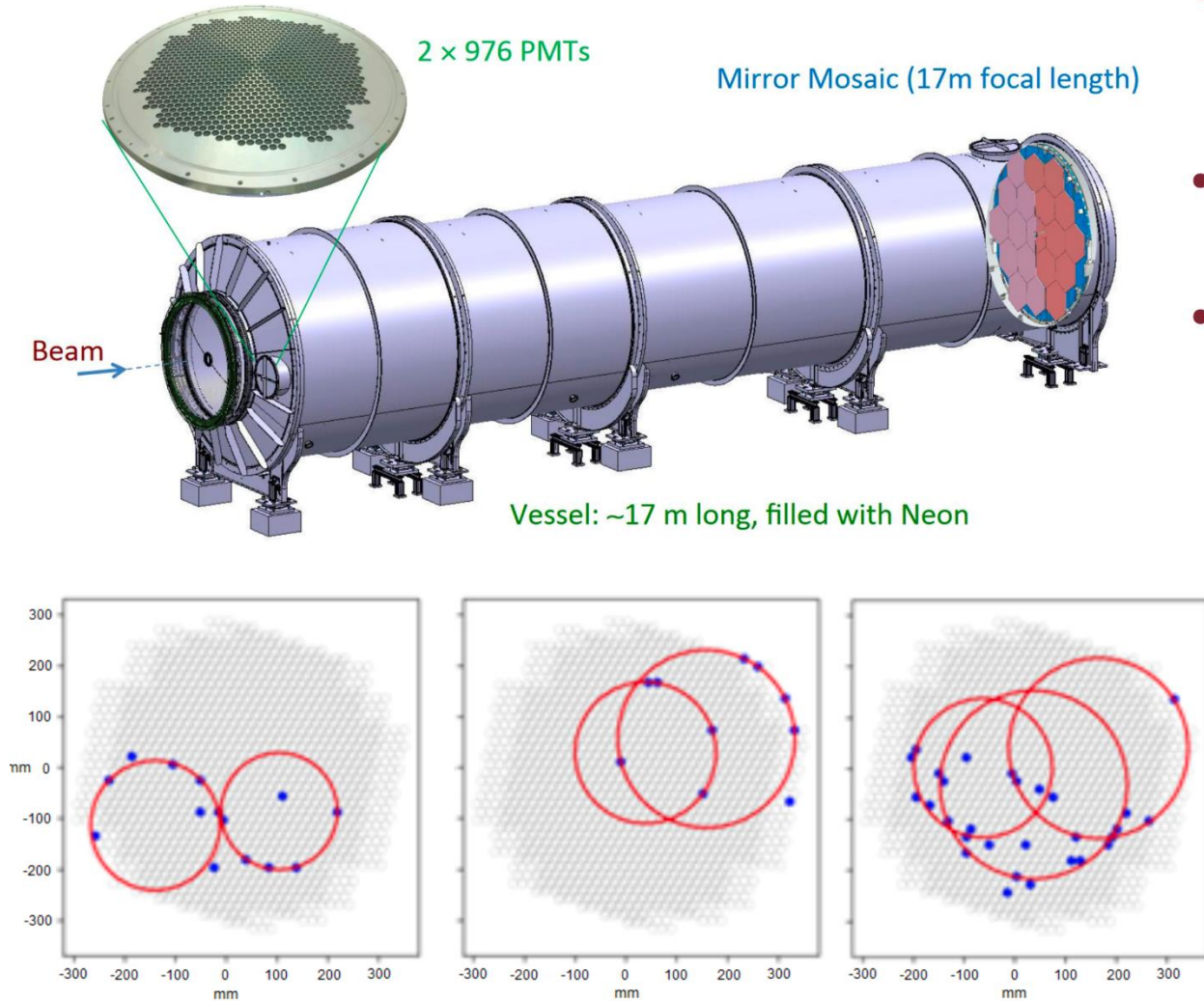
- Some detectors send raw data (***primitives***) to the FPGA-based level-0 trigger processor **L0TP**
- Primitives are generated from **TEL62 read out boards**
- L0TP **checks conditions (Masks)** to determine if an event should be selected and sent to L1
- Masks rely on the **physics information inside the primitives** (Energy, hit multiplicity, position, ...)

The NA62 Data Acquisition and Low Level Trigger

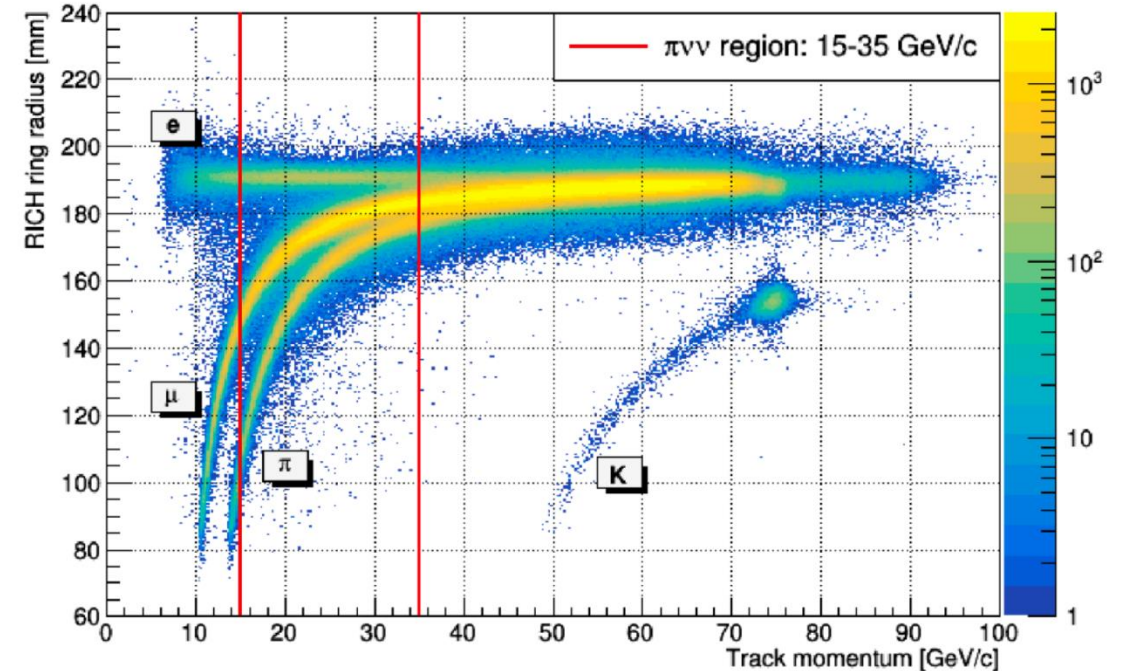


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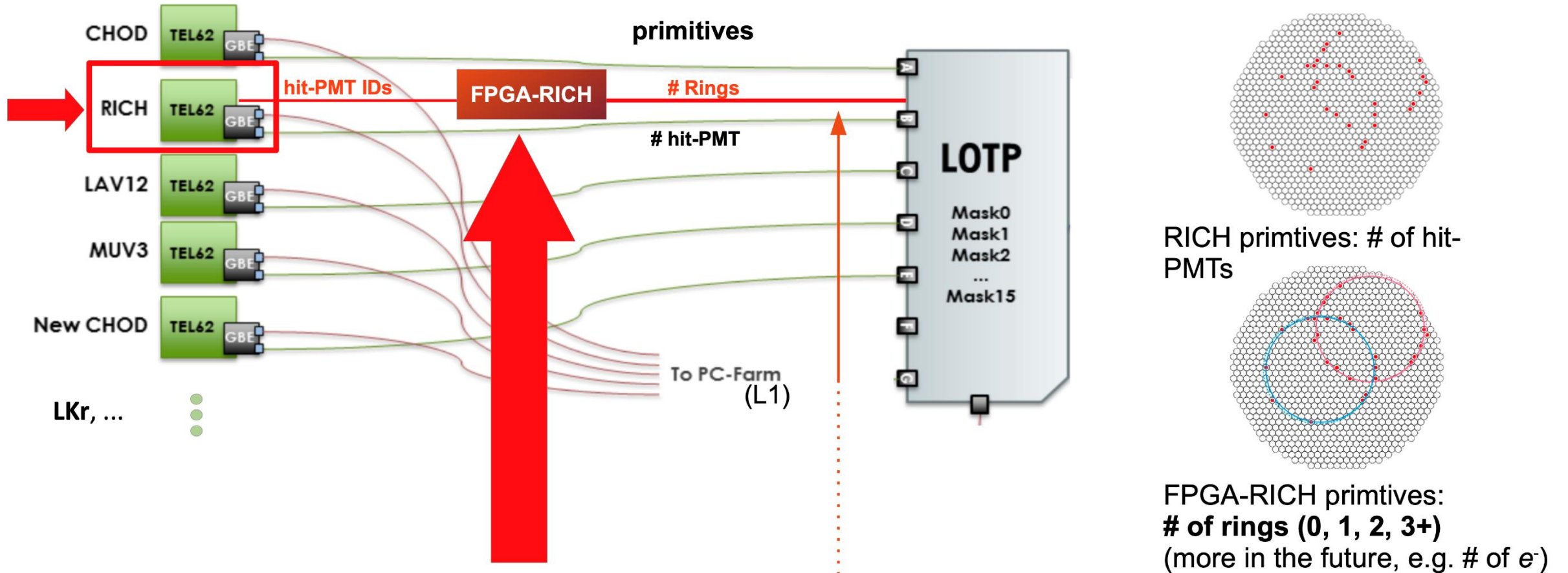
The NA62 Ring Imaging Cherenkov detector (RICH)



- During offline data analysis, it provides PID to distinguish between pions and muons from 15 to 35 GeV
- Uses the Cherenkov rings radius and track momentum
- **L0 primitives contain only number of HIT PMTs**

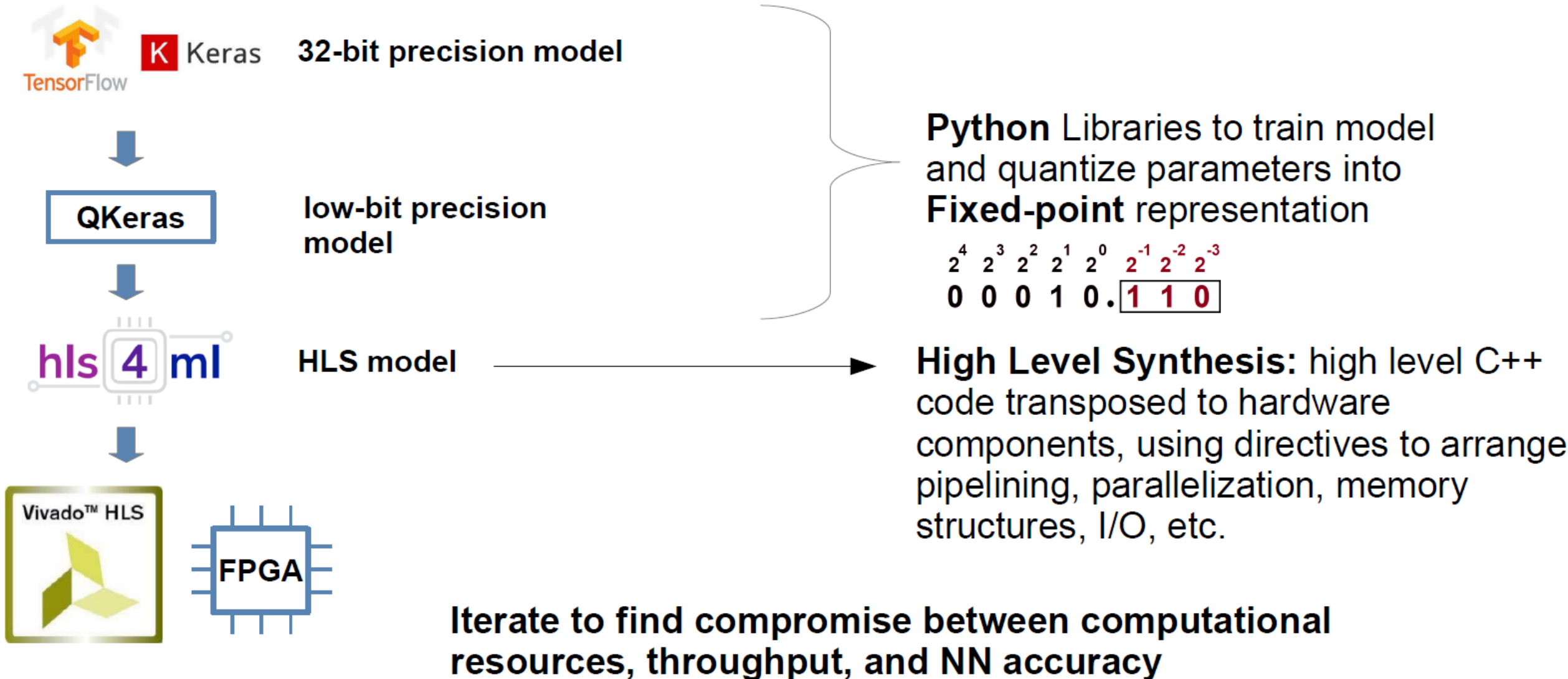


Smart Primitives: FPGA-RICH

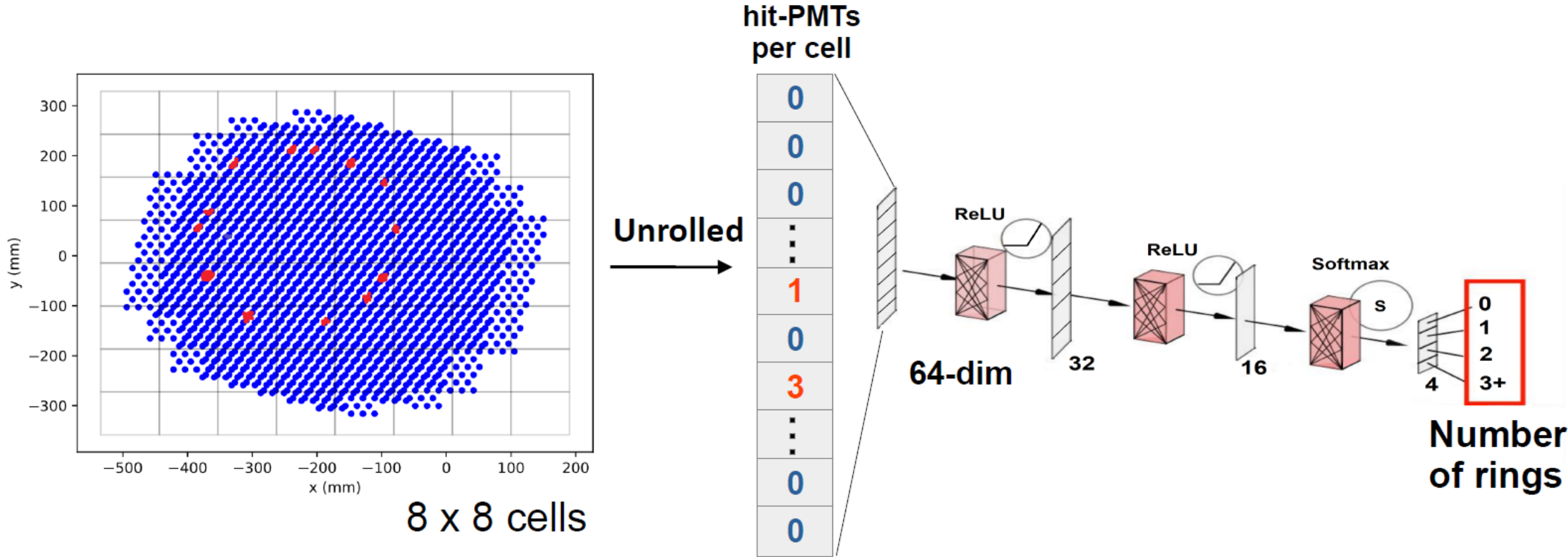


FPGA-RICH: reconstruct the rings geometry online using an AI algorithm on FPGA, to generate a **refined primitive stream** for L0TP selection masks

Workflow for Neural Networks deployment on FPGA



Neural Network Model (actually one of them...)

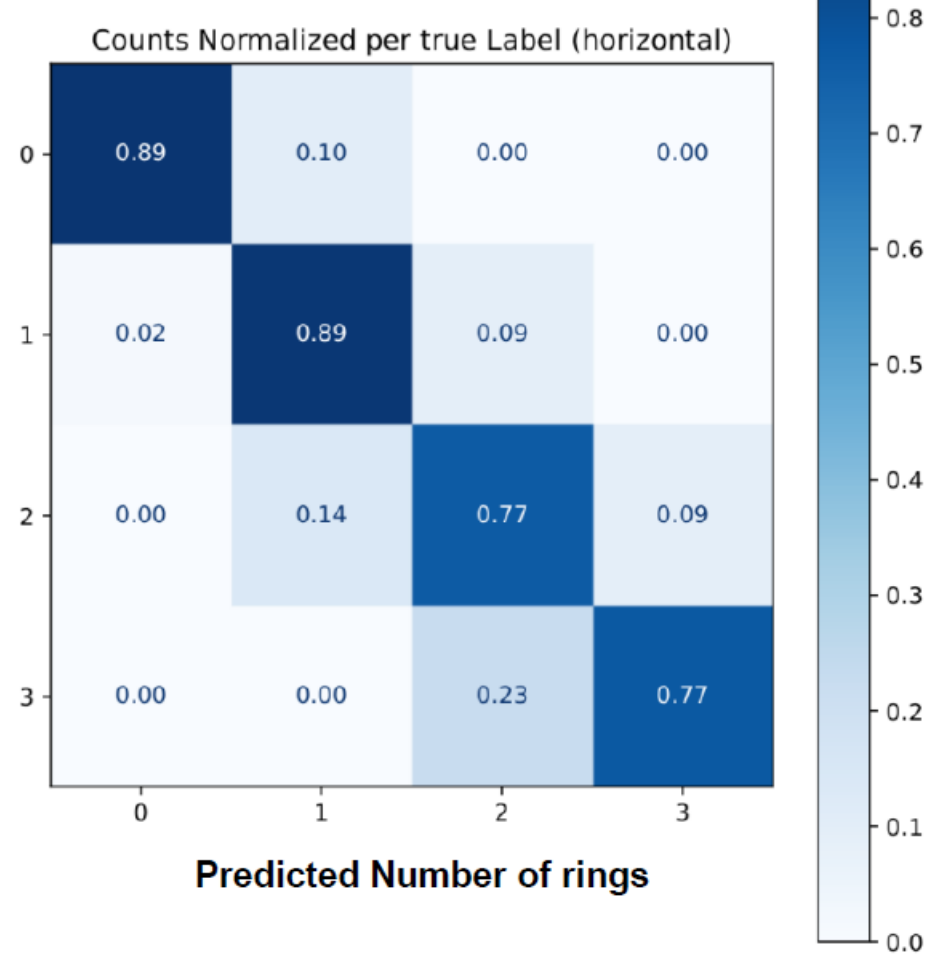
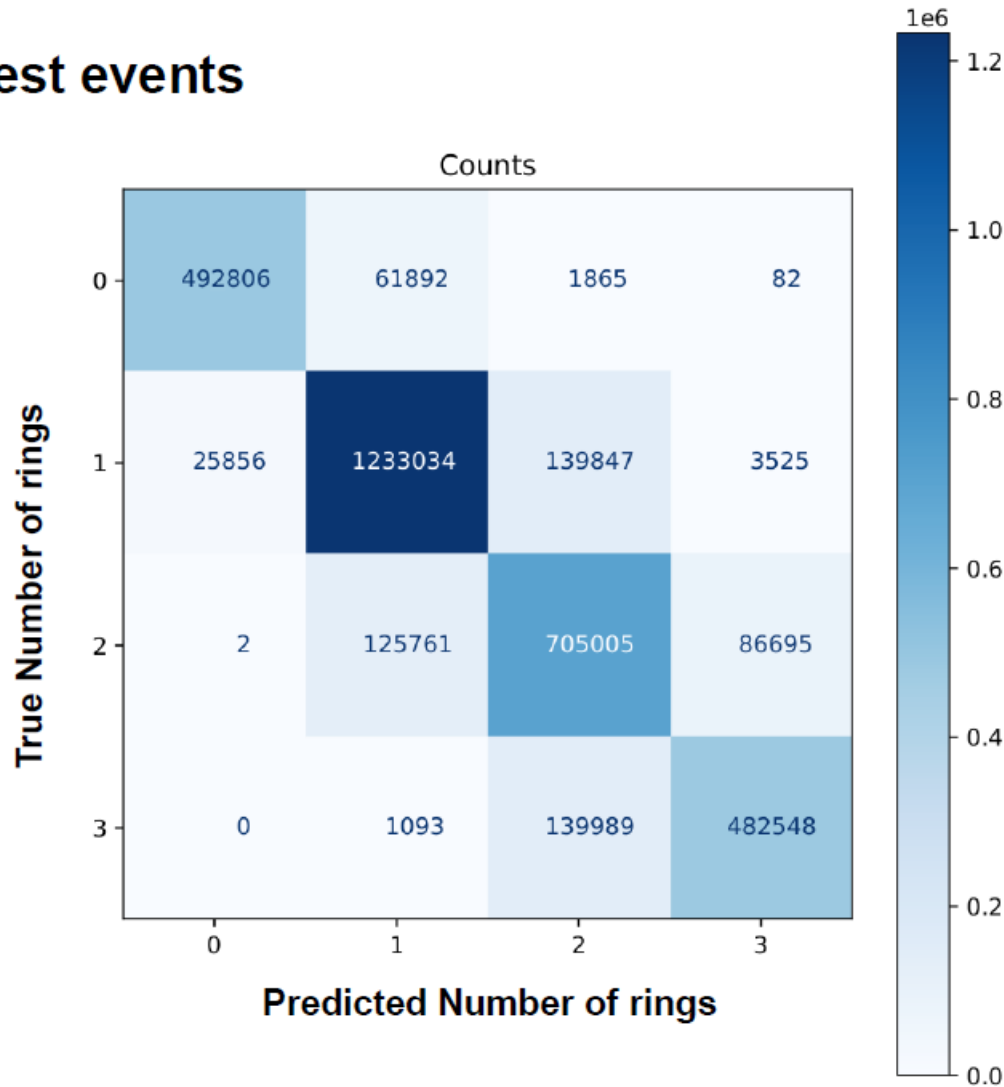


- Encoding of the PTMs geometrical positions in the input layer.

LUT = 14%
Flip-Flop = 6%
DSP = 7%
BRAM = 3%
on Versal VCK190

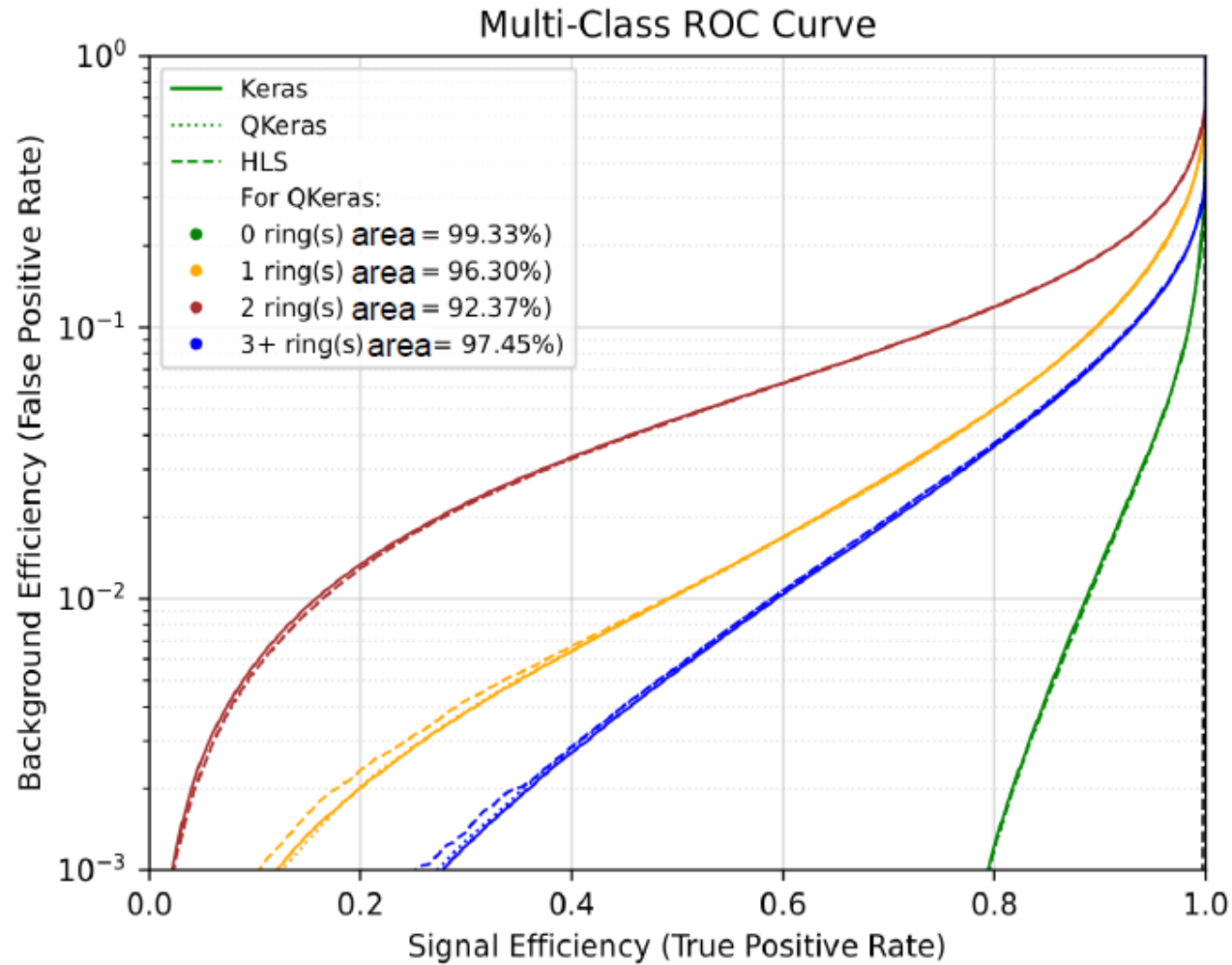
Neural Network Sensitivity

3.5 M test events



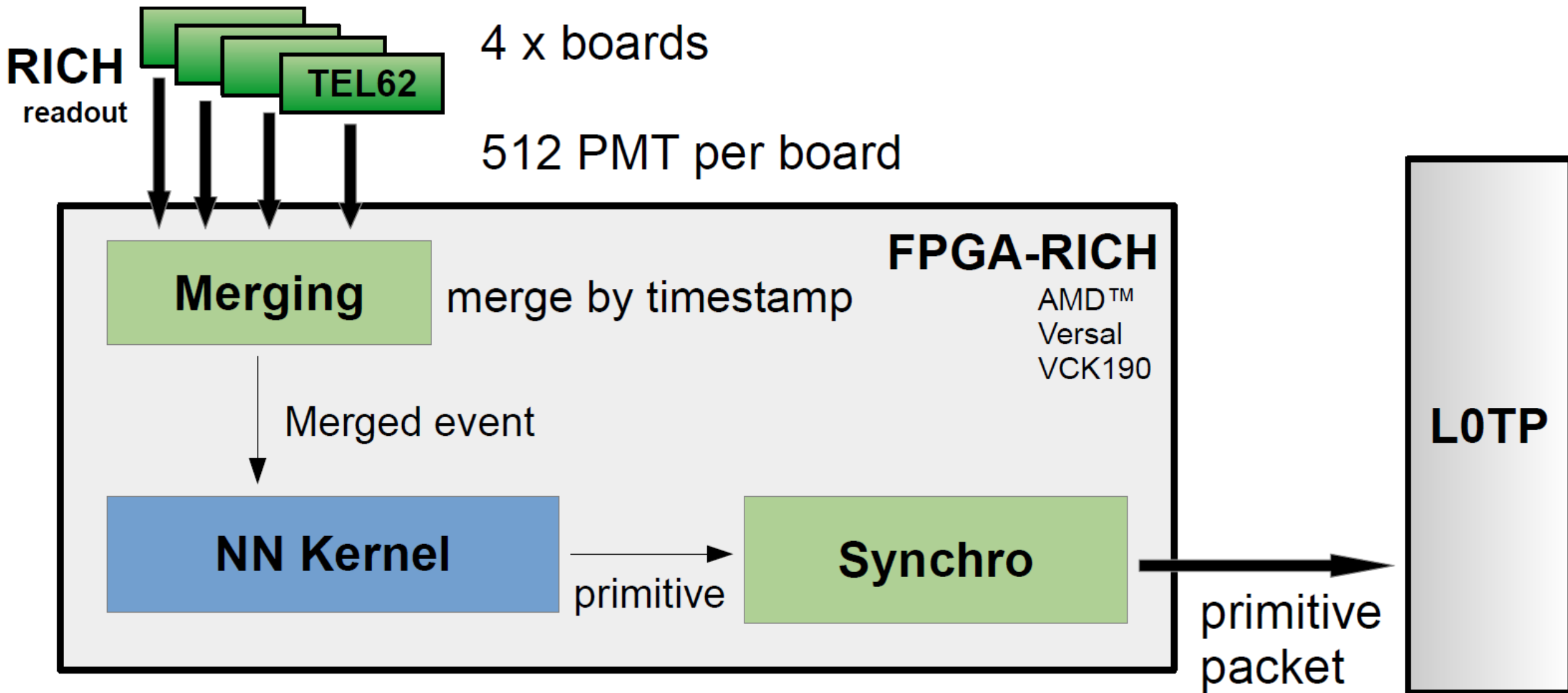
NN git: <https://baltig.infn.it/ape-lab/fpgarich>

ROC Curve, Throughput & Latency

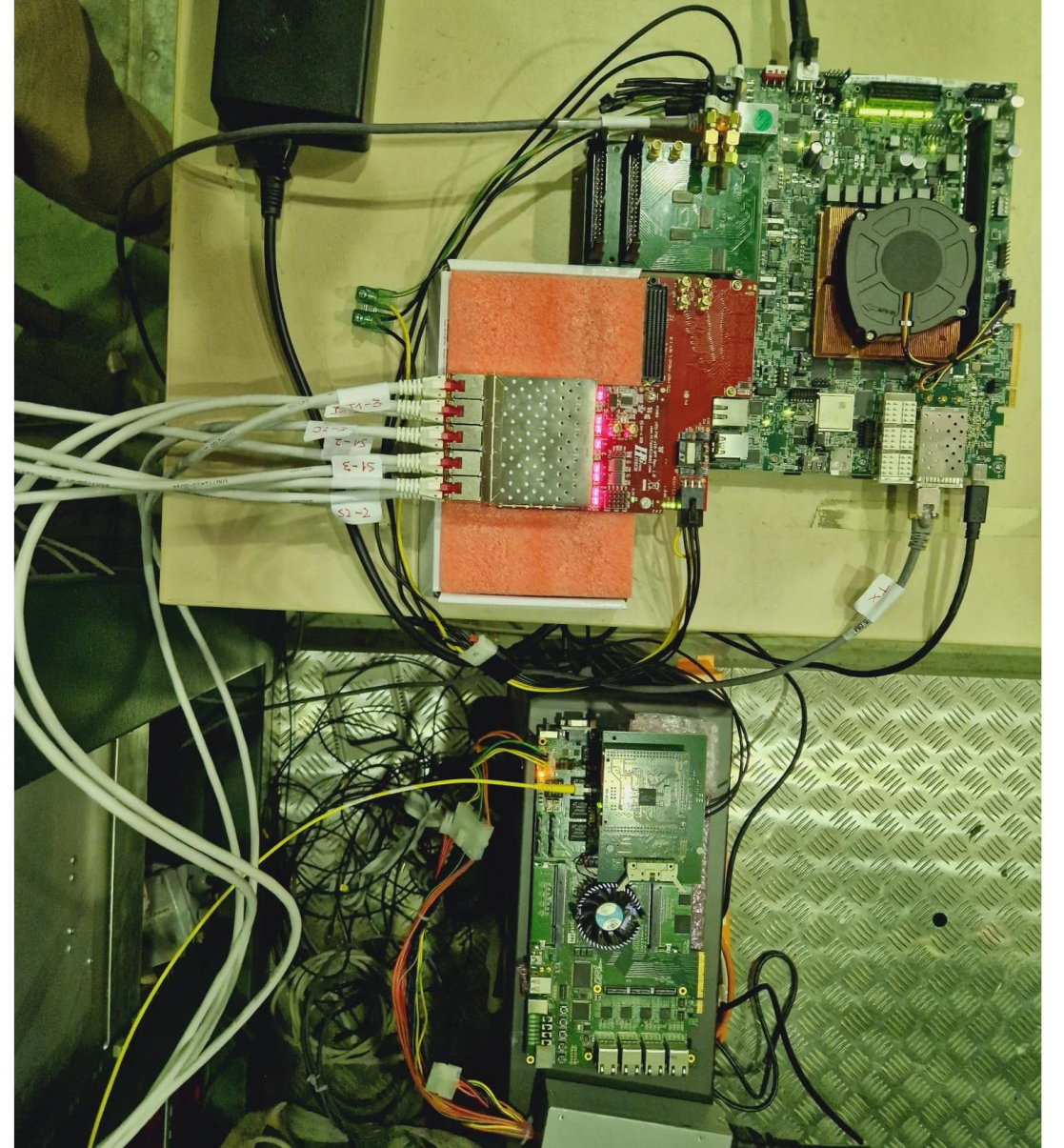
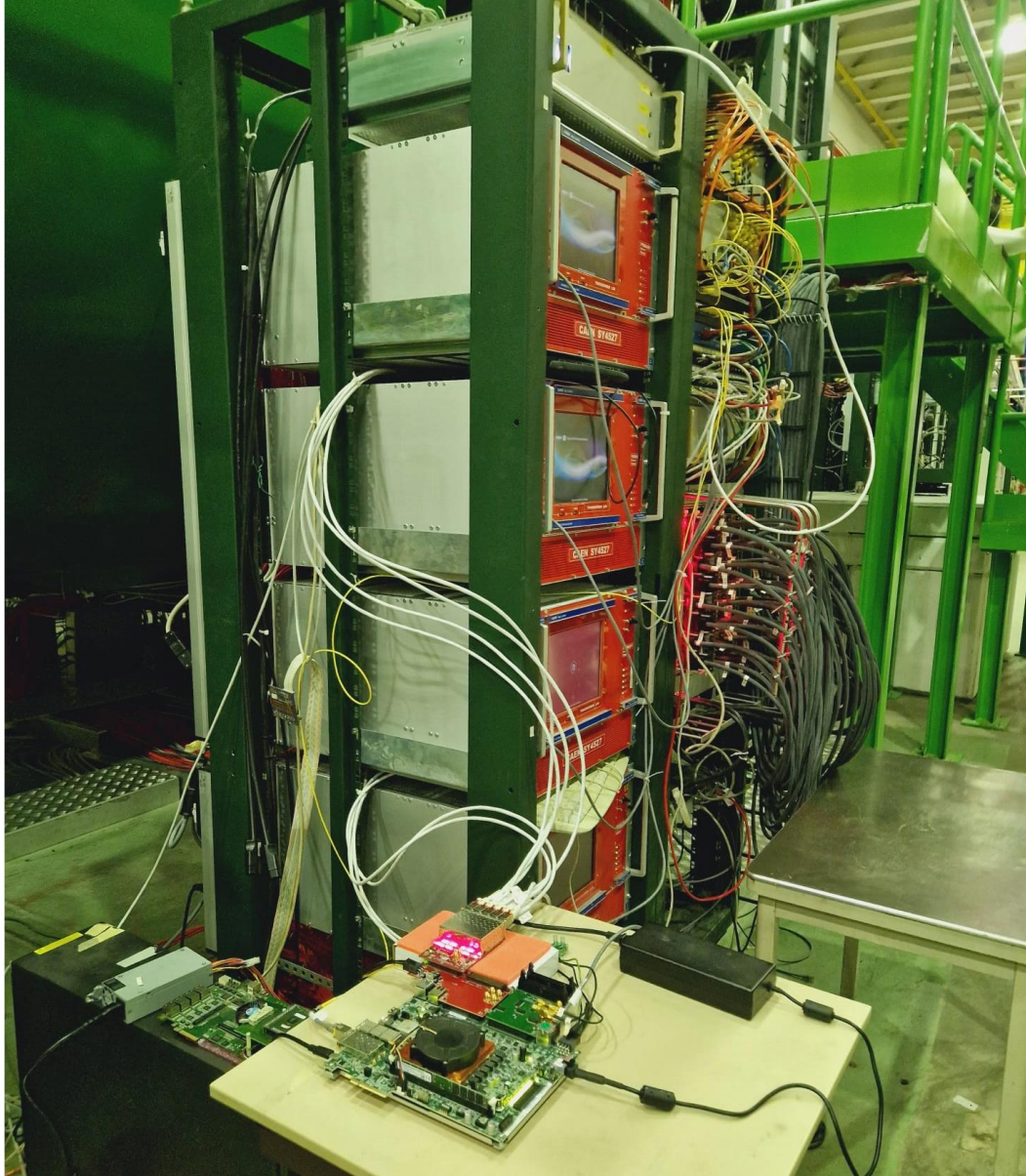


NN: avg Throughput \approx 21 MHz Latency = 160 ns at 300 MHz clock

Integration of the FPGA-RICH Pipeline

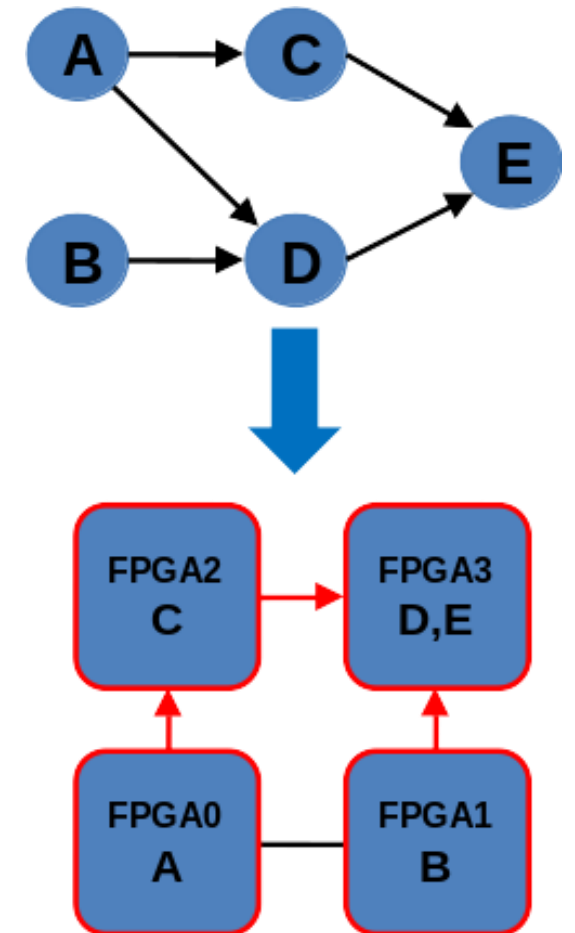


Integration of the FPGA-RICH Pipeline



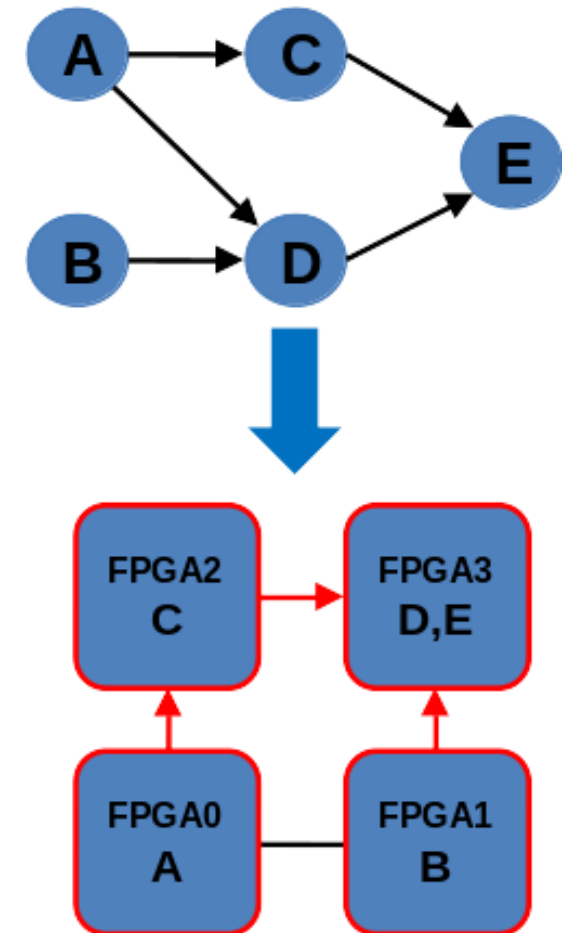
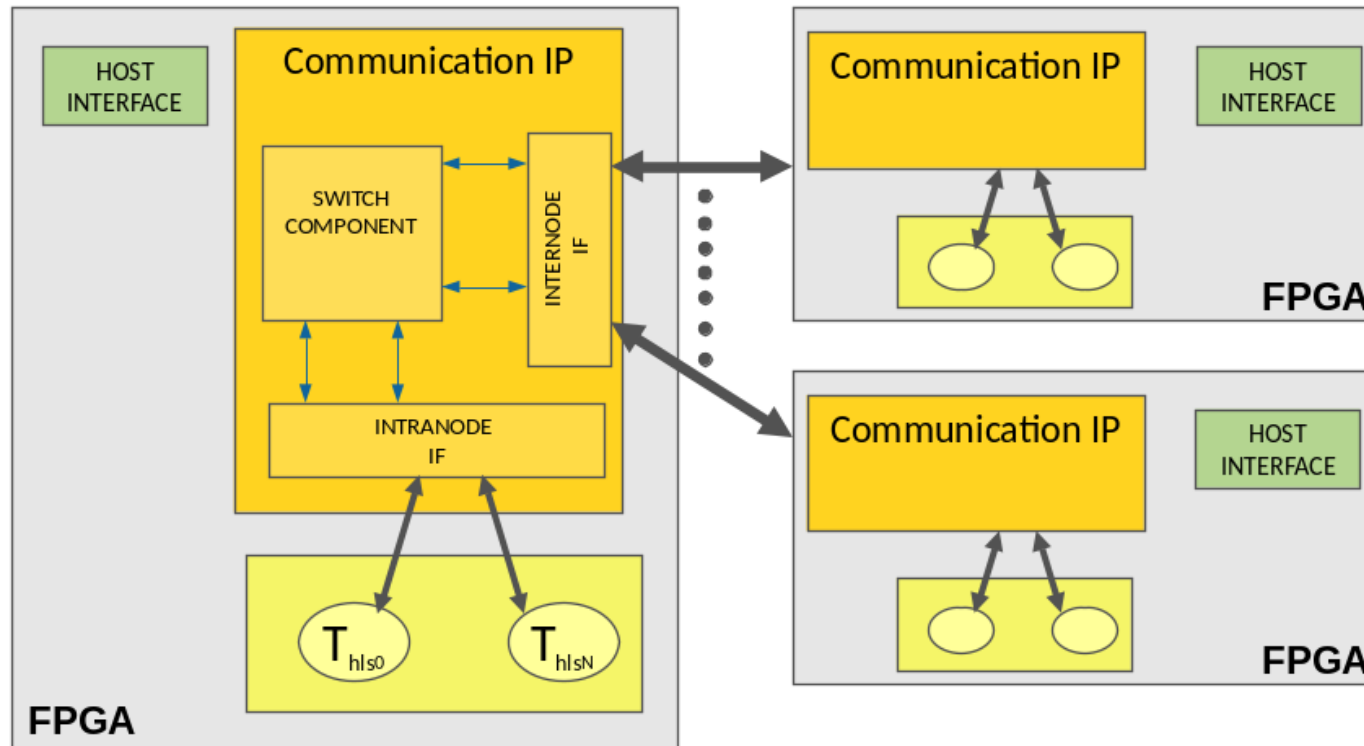
APEIRON: an overview

- **Goal:** develop a framework offering hardware and software support for the execution of real-time dataflow applications on a system composed by interconnected FPGAs .
 - Map the dataflow graph of the application on the distributed FPGA system and offers runtime support for the execution.
 - Allow users with no (or little) experience in hardware design tools, to develop their applications on such distributed FPGA-based platforms
 - Tasks are implemented in C++ using High Level Synthesis tools (Xilinx Vitis).
 - Lightweight C++ communication API
 - Non-blocking *send()*
 - Blocking *receive()*
 - **APEIRON is based on Xilinx Vitis High Level Synthesis framework and on INFN Communication IP (APE Router)**

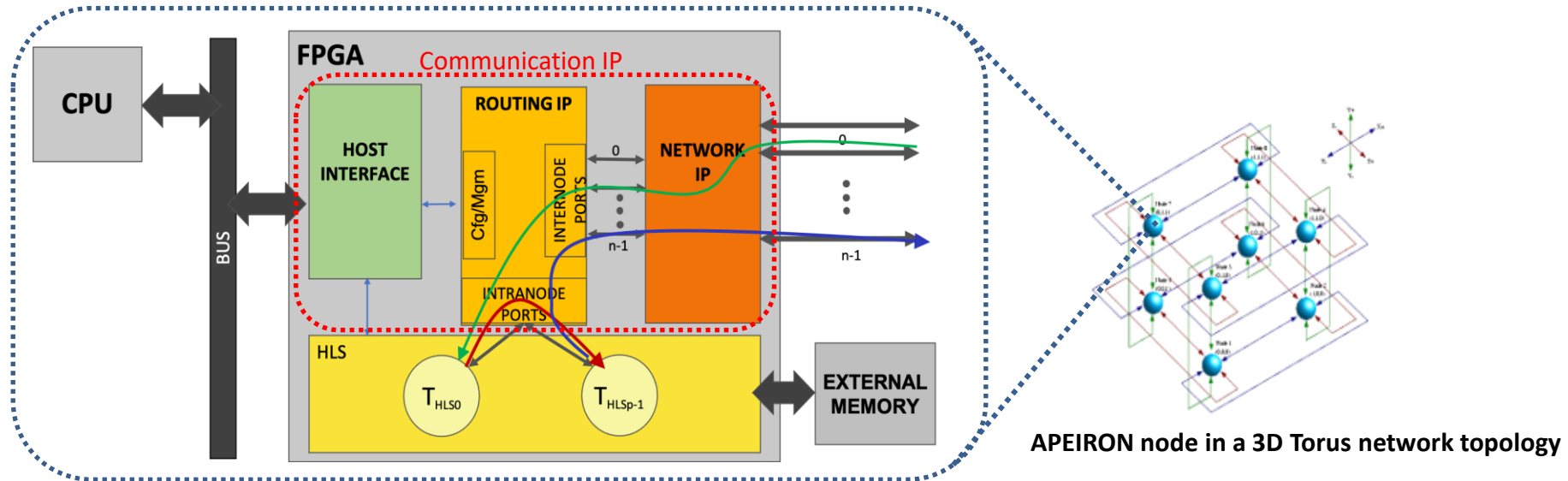


APEIRON: INFN Communication IP

- INFN is developing the IPs implementing a **direct network** that allows **low-latency** data transfer between processing tasks deployed on the same FPGA (intra-node communication) and on different FPGAs (inter-node communication).

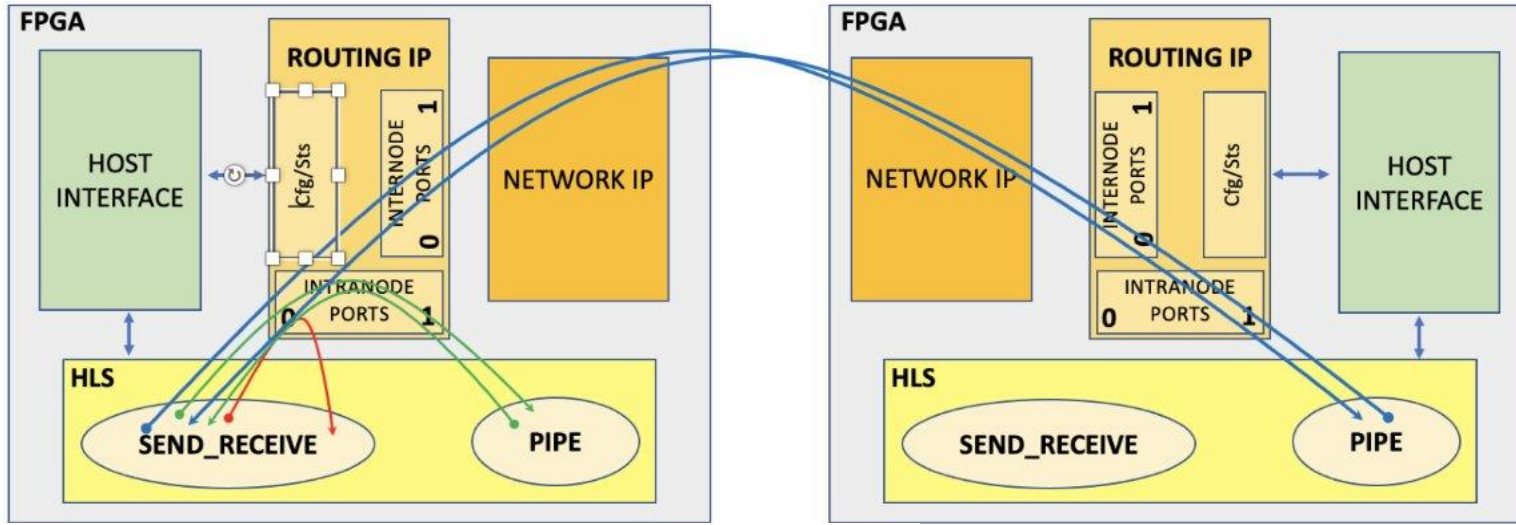


APEIRON: the Node

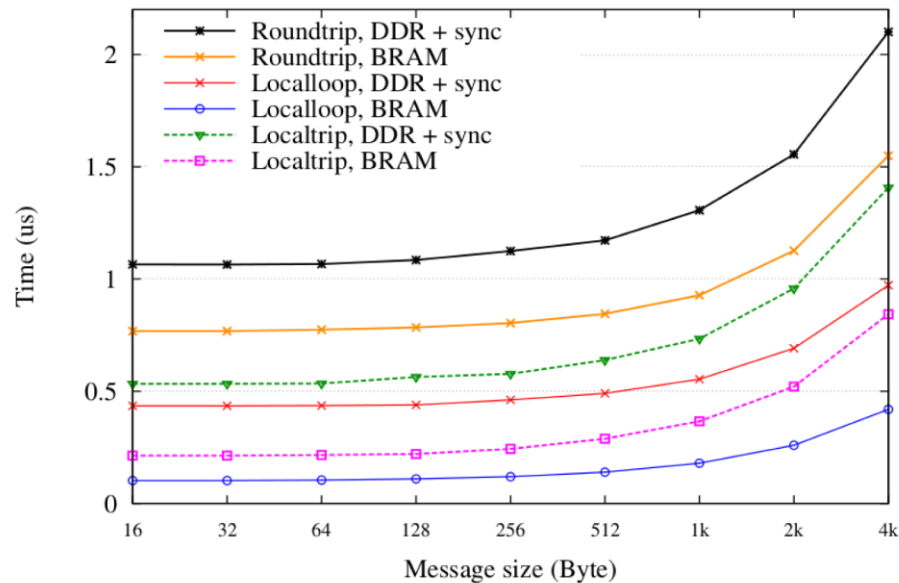


- **Host Interface IP:** Interface the FPGA logic with the host through the system bus.
 - Xilinx XDMA PCIe Gen3
- **Routing IP:** Routing of intra-node and inter-node messages between processing tasks on FPGA.
- **Network IP:** Network channels and Application-dependent I/O
 - APElink 40 Gbps
 - UDP/IP over 10 GbE
- **Processing Tasks:** user defined processing tasks (Xilinx Vitis HLS Kernels)

APEIRON: Communication Latency



Latency



Inter-node LATENCY (orange line) < 1us for packet sizes up to 1kB (source and destination buffers in BRAM)

Test modes

- Local-loop (red arrow)
- Local-trip (green arrows)
- Round-trip (blue arrows)

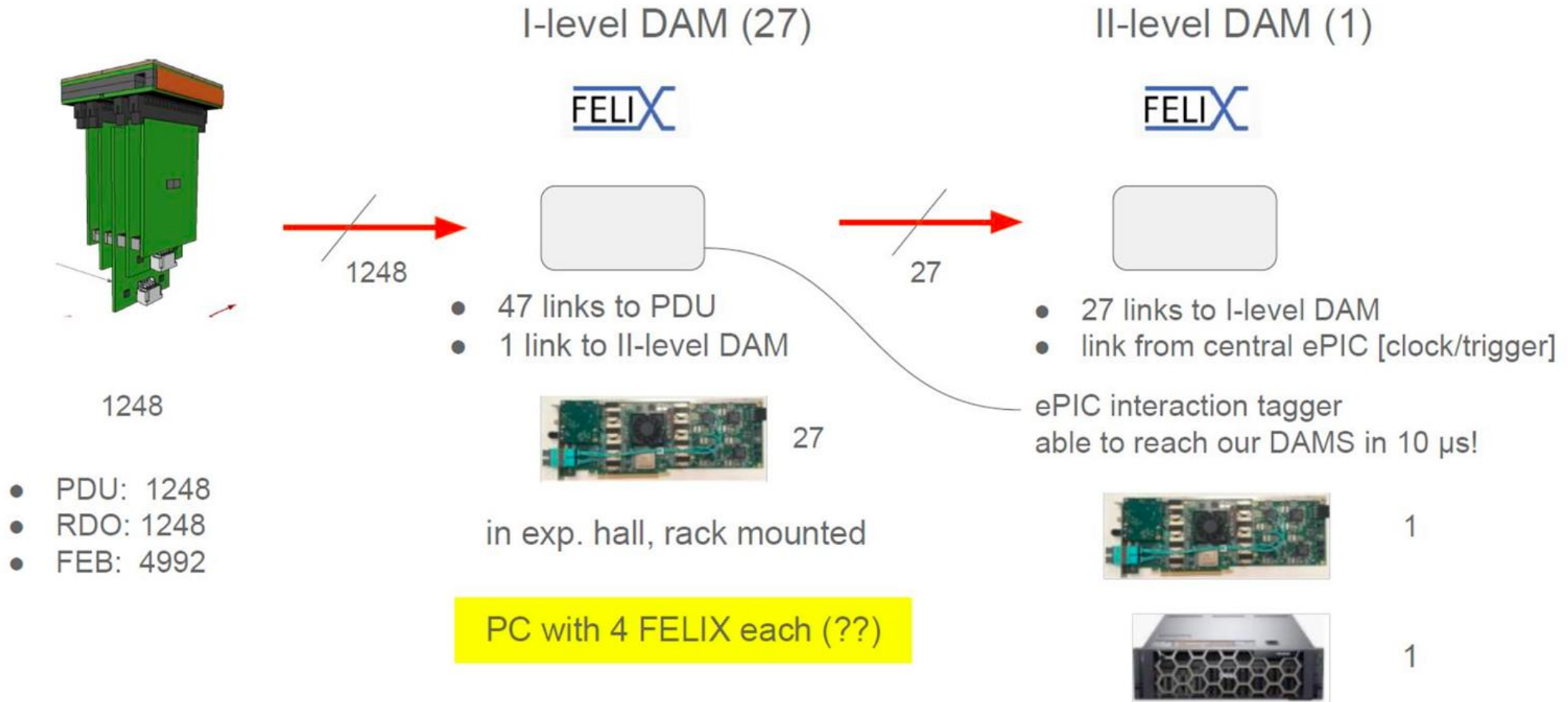
Test Configuration

- IP logic clock @ 200 MHz
- 4 intranode ports
- 2 internode ports
- 256-bit datapath width
- 4 lanes inter-node channels

RDO and ePIC DAQ

P. Antonioli

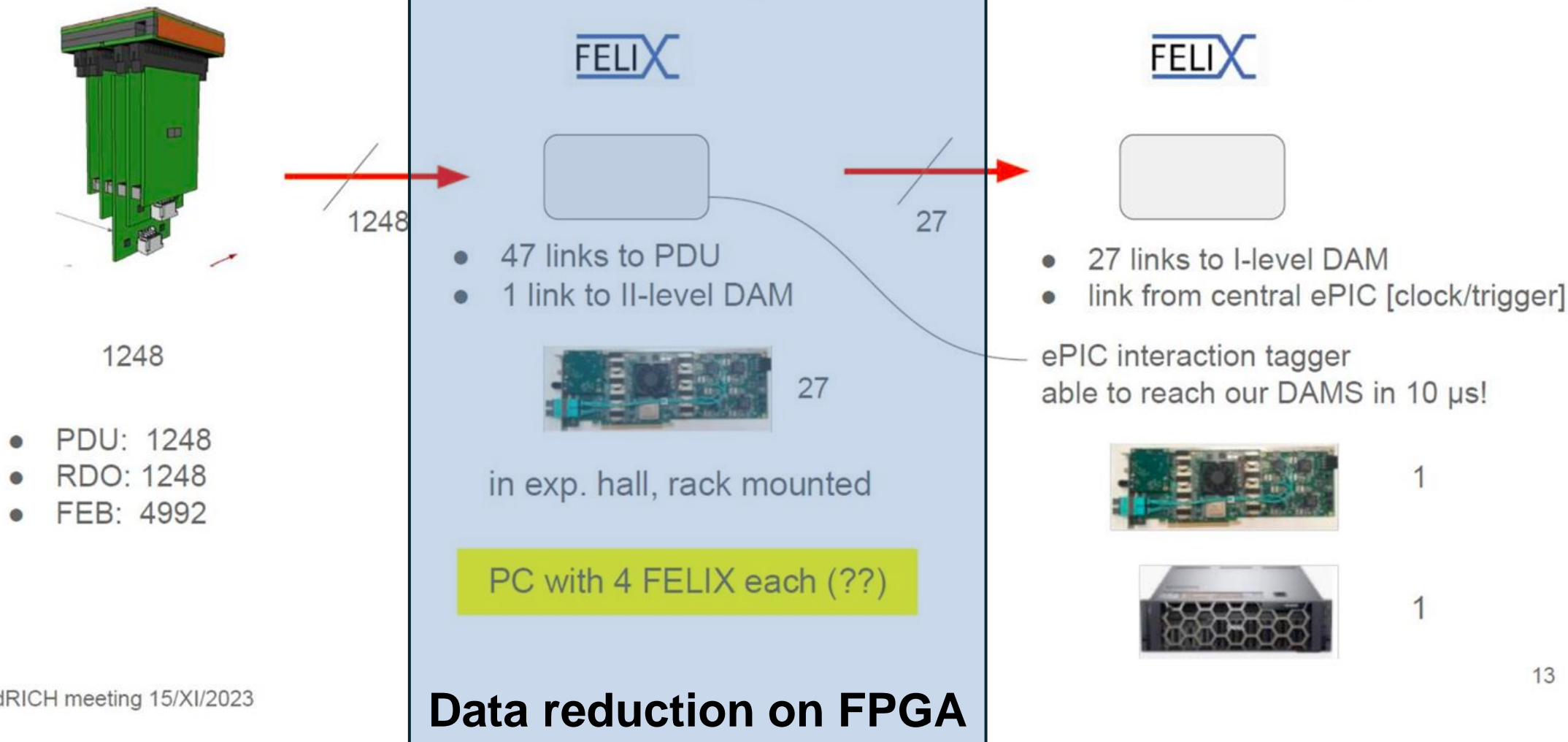
<https://indico.bnl.gov/event/20457/contributions/80658/attachments/49752/85138/20230914-DAQ.pdf>



RDO and ePIC DAQ

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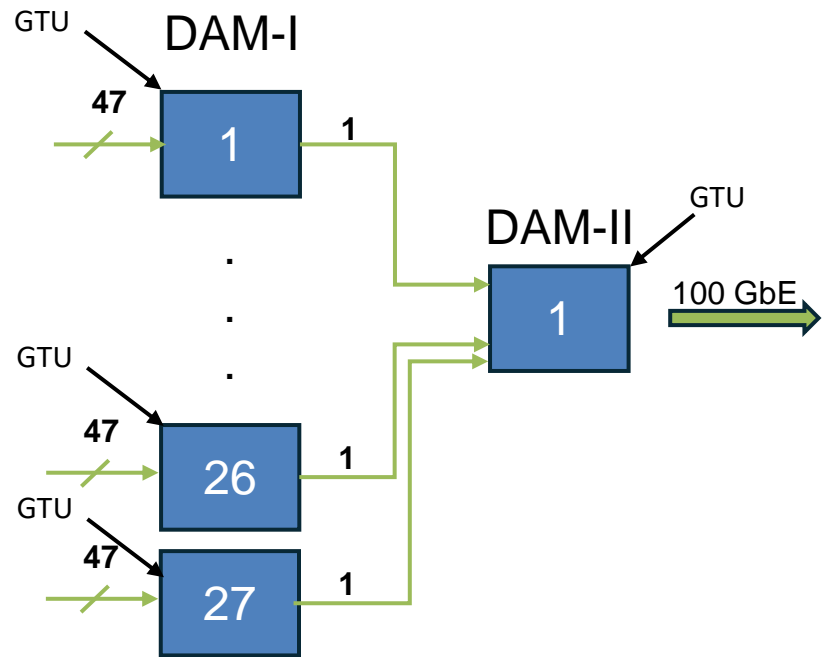
dRICH Data Reduction Stage on FPGA

- Objective: design of a data reduction stage for the dRICH with a ~ 100 data bandwidth reduction in DAM-I level output to DAM-II level input.
- Make exclusive use of DAQ components (Felix DAMs)
 - Add few DAM units wrt the bare minimum needed to readout the 1248 RDO links to implement a distributed processing scheme.
 - Integration with the Interaction Tagger to boost performance and enable other features.
- Online Signal/Background discrimination using ML
 - Collecting datasets using data available from simulation campaigns
 - Background:
 - e/p with beam pipe gas
 - Synchrotron radiation (MC only?)
 - Merged: signal + e/p with beam pipe gas background (full), few events
 - SiPM Noise
 - DCR modelled in the reconstruction stage
 - Spatial and time dependency of the rate?

dRICH Data Reduction Stage on FPGA

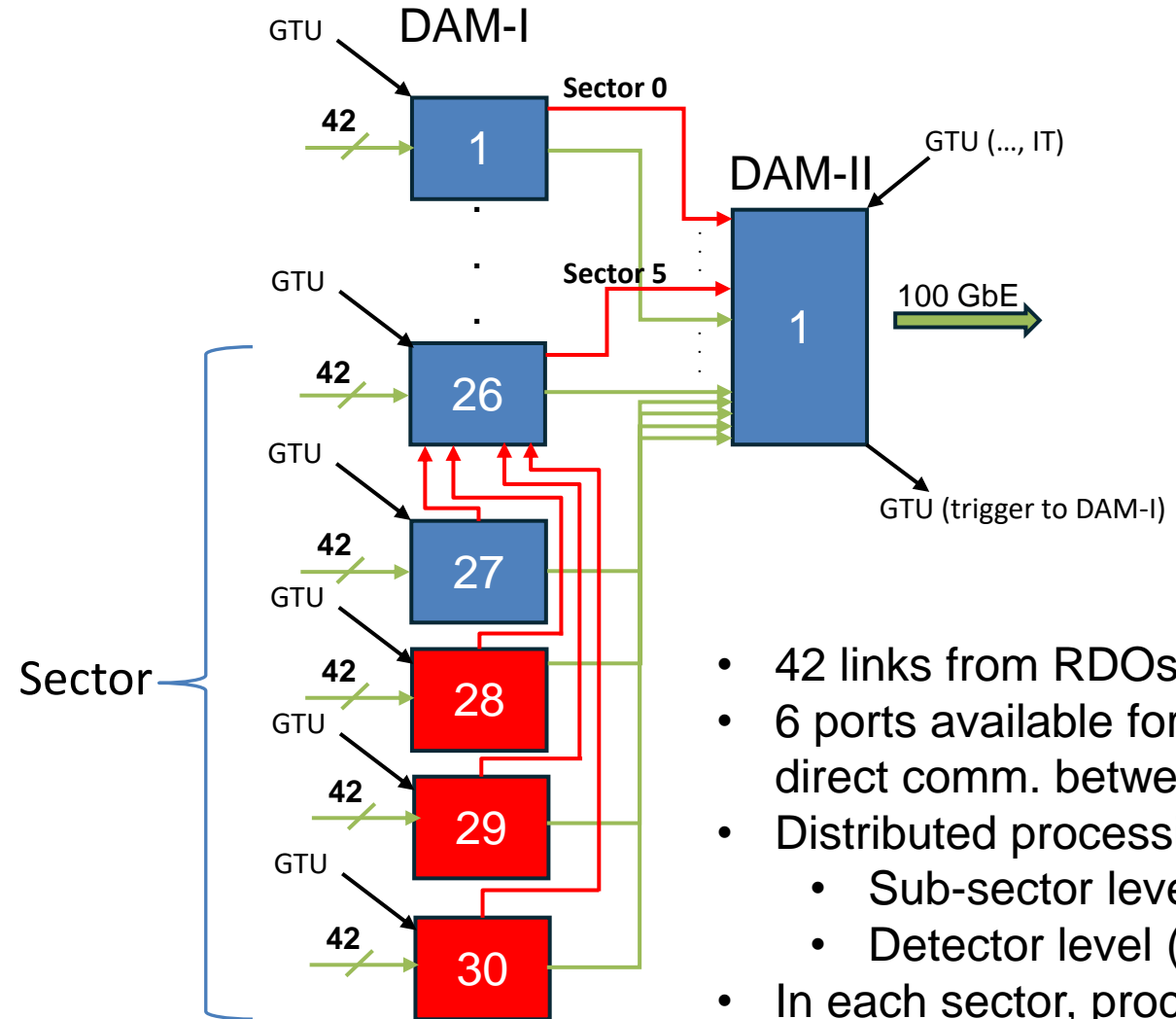
- Online Signal/Background discrimination using ML (continued)
 - Study of Inference Models
 - Restricting our study to inference models that can be deployed on FPGA with reasonable effort (using a High-Level Synthesis workflow)
 - MLP, CNN, GNN NN Models (HLS4ML)
 - BDT (Conifer)
 - Inference throughput (98.5 MHz) is the main concern.
 - HDL optimized implementation is an option.
 - Deployment on multiple Felix DAMs directly interconnected with the APE communication IPs

dRICH Data Reduction Stage on FPGA: example deployment



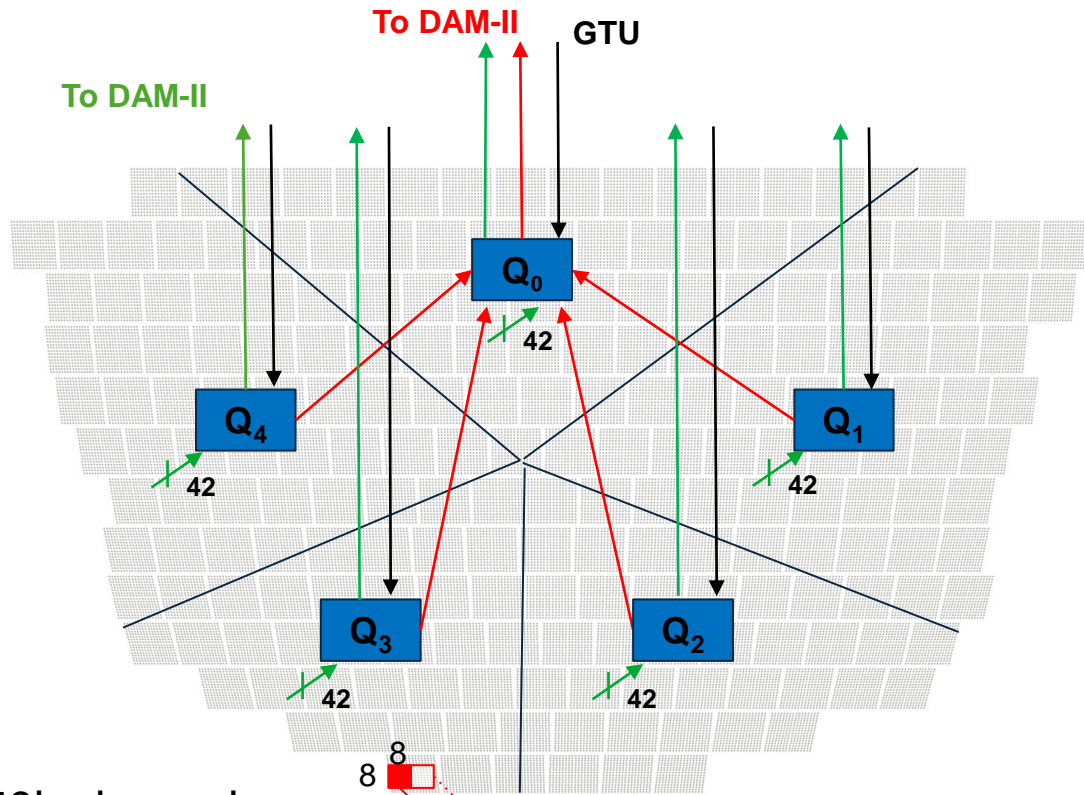
RDO Data

Processed Data



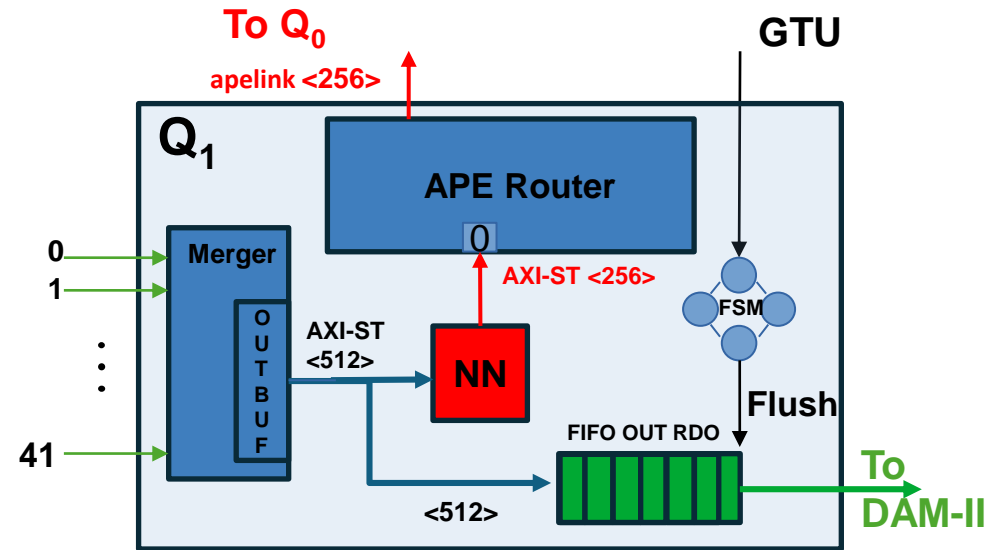
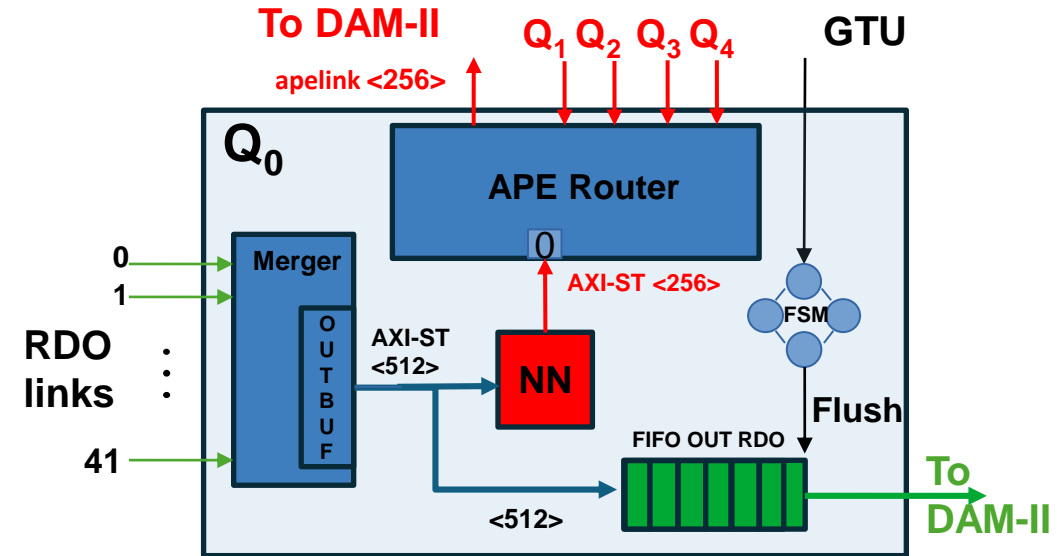
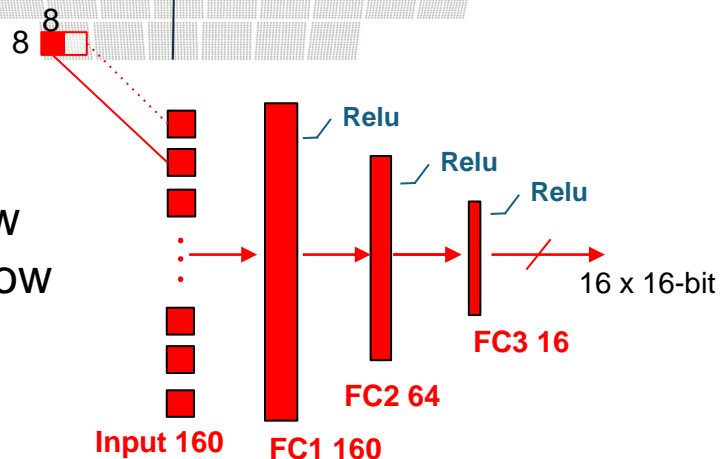
- 42 links from RDOs
- 6 ports available for direct comm. between DAMs
- Distributed processing
 - Sub-sector level (DAM-I)
 - Detector level (DAM-II)
- In each sector, processed data routed by one DAM-I to DAM-II

dRICH Data Reduction Stage on FPGA: example deployment

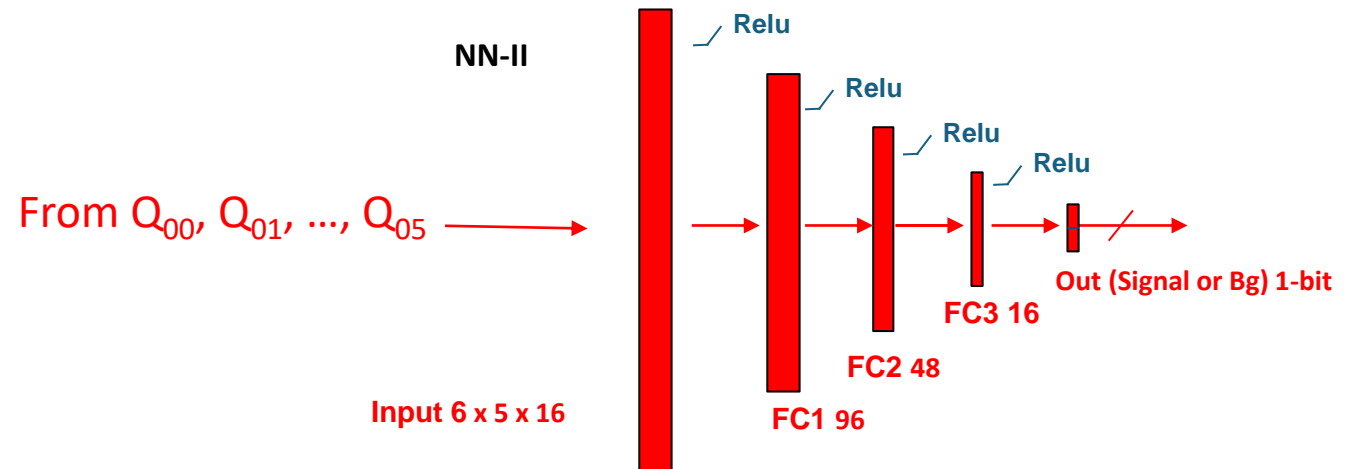
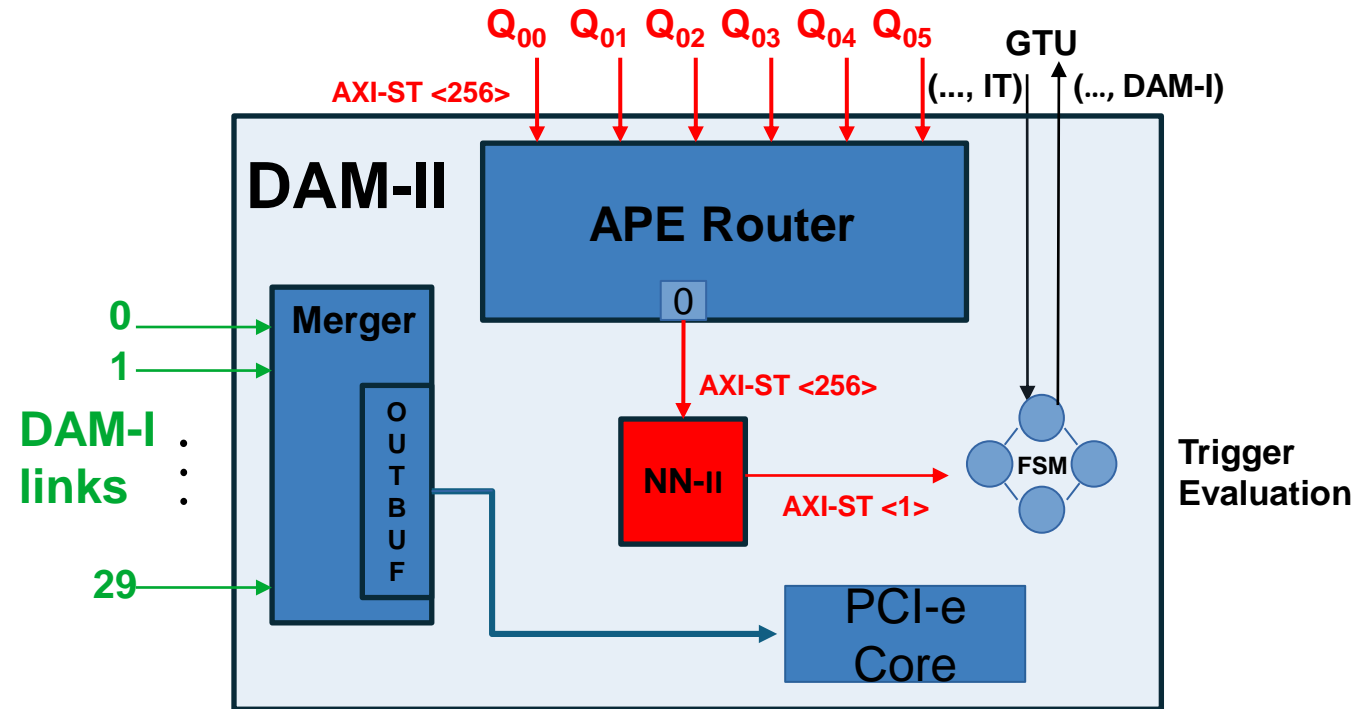
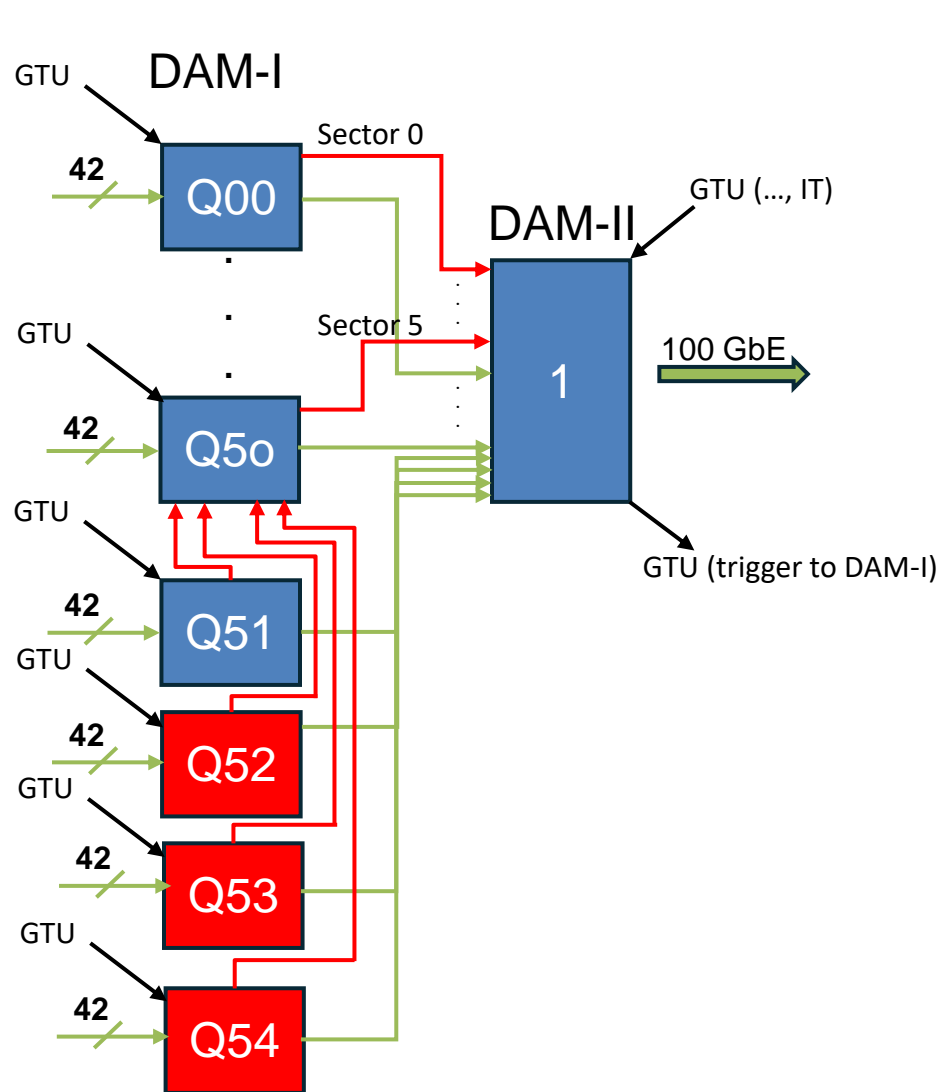


50k channels per sector

- RDO flow
- PROC flow
- GTU I/O



dRICH Data Reduction Stage on FPGA: example deployment



Current status and outlook

- We have started collecting datasets and experimenting with inference models.
- Details of the final deployment will be affected by several factors
 - Final selection on the inference model(s): BDT, MLP, CNN, GNN, ...
 - Net amount of FPGA resources available (discounting the “standard” DAQ firmware) in DAMs.
 - Actual additional DAQ resources (DAMs, ...) dedicated to the data reduction system.
- Possible additional features
 - Provide services (statistics) for the online monitoring.
 - Having track seeds information from the Interaction Tagger could enable more sophisticated features
 - Particle counting
 - Particle identification
 - We have devised a method to tag reconstructed events with PIDs.

Backup Slides

Bandwidth analysis		Limit	Comments
INPUT	Sensor rate per channel [kHz]	300,00	4.000,00
	Rate post-shutter [kHz]	55,20	800,00
	Throughput to serializer [Mb/s]	34,50	788,16
	Throughput from ALCOR64 [Mb/s]	276,00	limit FPGA dependent: with RDO prototype we will have something
	Throughput from RDO [Gb/s]	1,08	12,70 based on Microchip
	Input at each DAM I [Gbps]	49,59	584,20
	Buffering capacity at DAM I [MB]	0,01	to be checked but seems manageable
	Throughput from DAM I to DAM II [Gbps]	0,25	12,70 this might be higher (from FELIX to FELIX)
	Output to each DAM II [Gbps]	6,70	342,90

} ALCOR

} RDO

This is the aggregated number we could sell

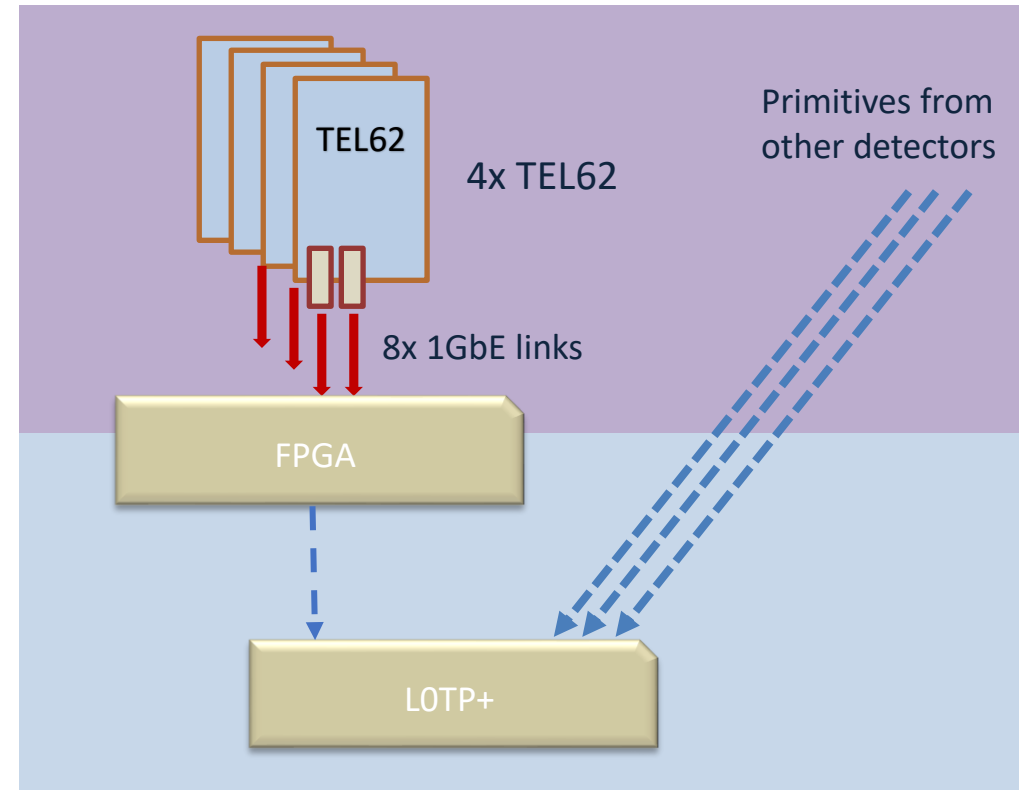
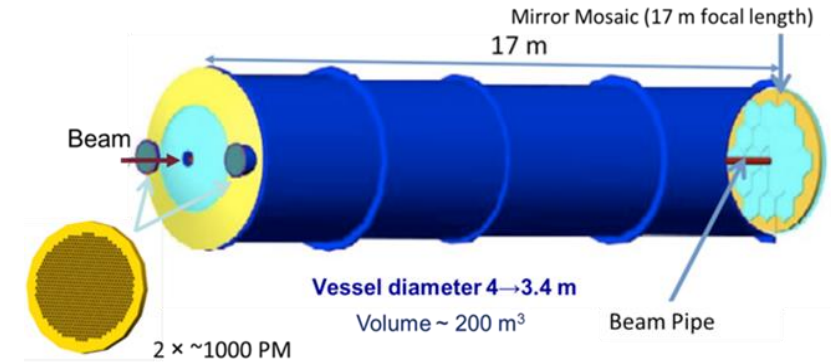
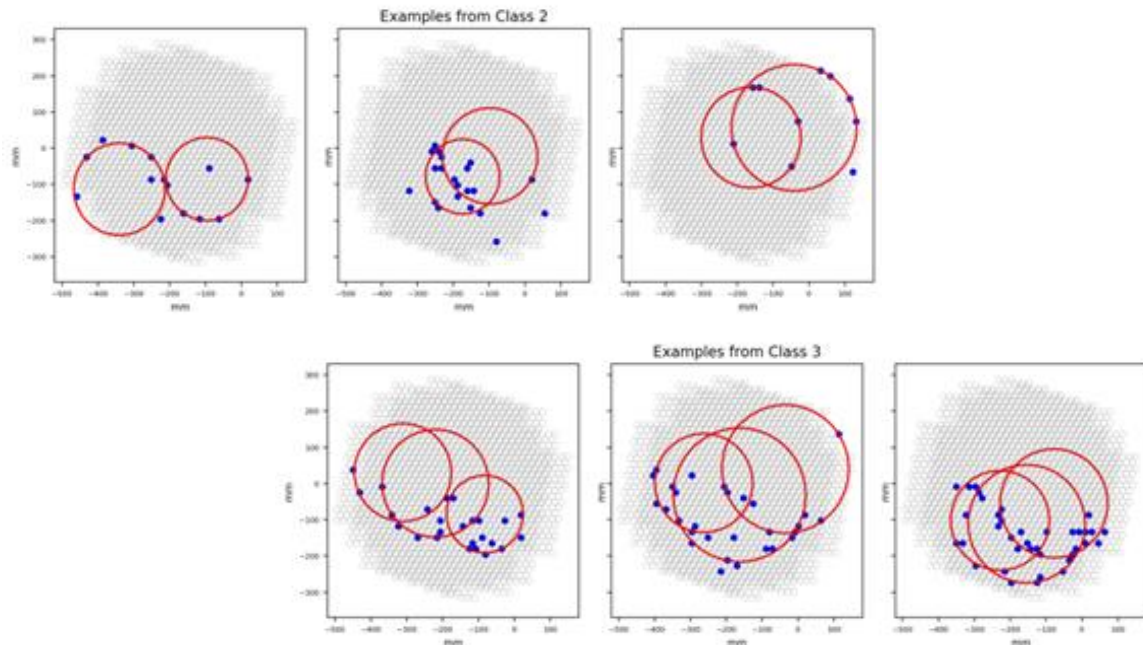
Aggregated dRICH data		Comments
Total input at DAM I [Gb/s]	1.339,03	This is only "inside" DAM, not to be transferred on PCI
Total input at DAM II [Gb/s]	6,70	This is based on aggregation above + reduction factor of the interaction tagger
Total output from DAM II [Gb/s]	6,70	Further reduction possible to be investigated (FPGA level?)

Note: first hard limit (RDO-DAM link) hit only at 3 MHz input..

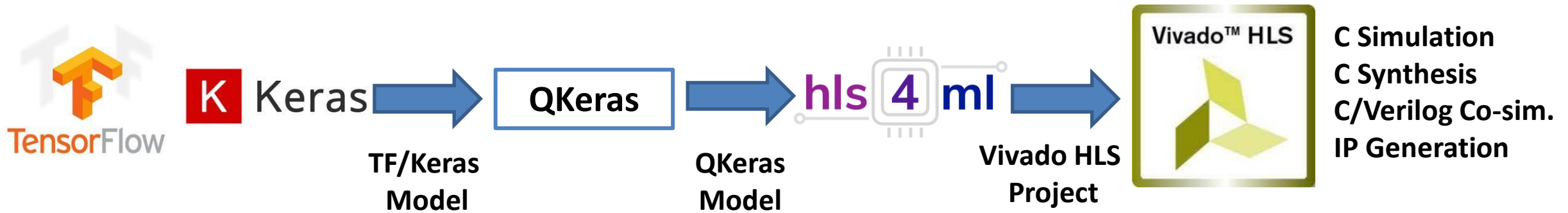
But we should think how to present things... (see next slide)

PID in NA62 with the RICH using NN on FPGA at L0 Trigger

- Goal: for any event detected by the RICH provide an estimate for the **number charged particles** and the **number of electrons**
- Streaming readout processing on FPGA using Neural Networks for classification (10 MHz).
- Produce a new primitives stream for L0TP+
- **The main challenge is the proc. throughput**



Design and Implementation Workflow

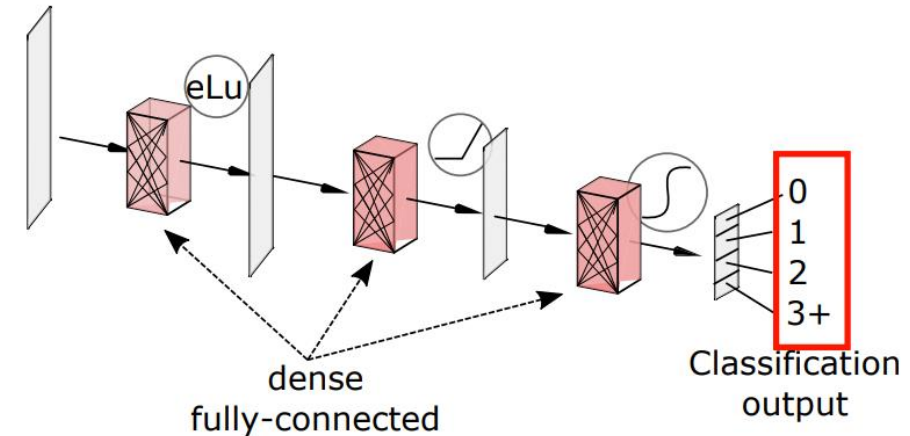


Design targets (efficiency, purity, throughput, latency) and constraints (mainly FPGA resource usage) must be taken into account and verified at any stage:

- Generation strategy of training and validation data sets.
- **TF/KERAS** NN architecture (number and kind of layers) and representation of the input
 - Training strategy (class balancing, batch sizes, optimizer choice, learning rate,...).
- **QKeras** Search iteratively the minimal representation size in bits of weights, biases and activations, possibly by layer.
- **hls4ml** Tuning of REUSE FACTOR config param (low values -> low latency, high throughput, high resource usage), clock frequency.
- **Vivado HLS** co-simulation for verification of performance (experimented very good agreement with QKeras Model)

NN Architectures: Dense Model

- **Input representation: normalized hitlist (max 64 hits per event)**
- **Output: 4 classes (0, 1, 2, 3+ rings)**
- **Quantization (fixed point)**
 - Weights and biases: 8 bits $\langle 8, 1 \rangle$
 - Activations: 16 bits $\langle 16, 6 \rangle$
- **FPGA resource usage (VCU118)**
LUT 14%, DSP 2%, BRAM 0%
- **Latency: 22 cycles @ 150MHz**
- **Initiation Interval (II): 8 cycles**
- **Throughput: 18.75 MHz**

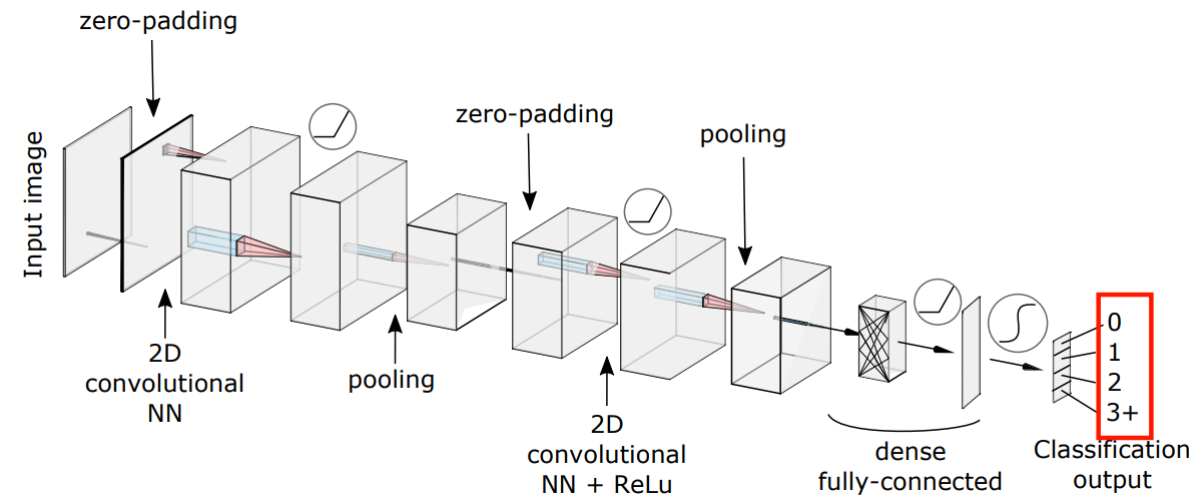
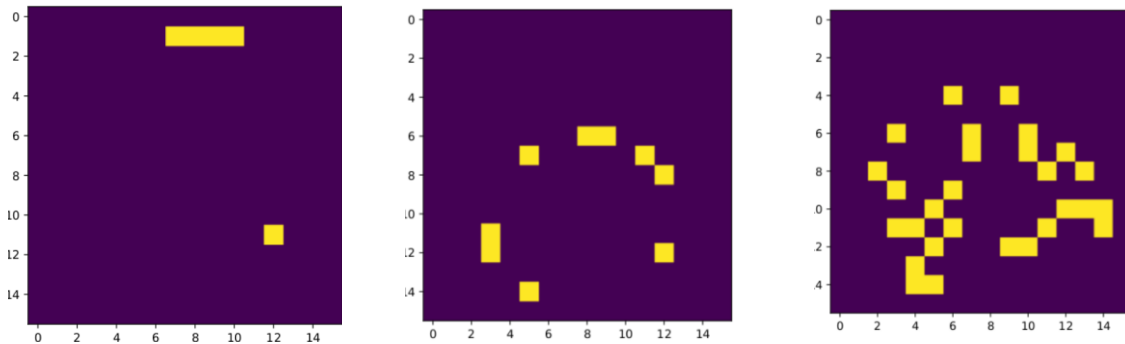


Layer (type)	Output Shape	Param #
input1 (InputLayer)	[None, 64]	0
fc1 (Dense)	(None, 64)	4160
act1 (Activation)	(None, 64)	0
fc2 (Dense)	(None, 16)	1040
act2 (Activation)	(None, 16)	0
fc3 (Dense)	(None, 4)	68
softmax (Activation)	(None, 4)	0

=====
Total params: 5,268

NN Architectures: Convolutional Model

- Input representation: 16x16 images
- Output: 4 classes (0, 1, 2, 3+ rings)
- Quantization (fixed point):
 - Weights and biases: 8 bits $\langle 8, 1 \rangle$
 - Activations: 16 bits $\langle 16, 6 \rangle$
- FPGA resource usage (Alveo U200)
 - LUT 5.2%, FF 1.5%, DSP 4.8%, BRAM 0.05%
- Latency: 388 cycles @ 220MHz
- Initiation Interval (II): 369 cycles
- Throughput: 0.6 MHz

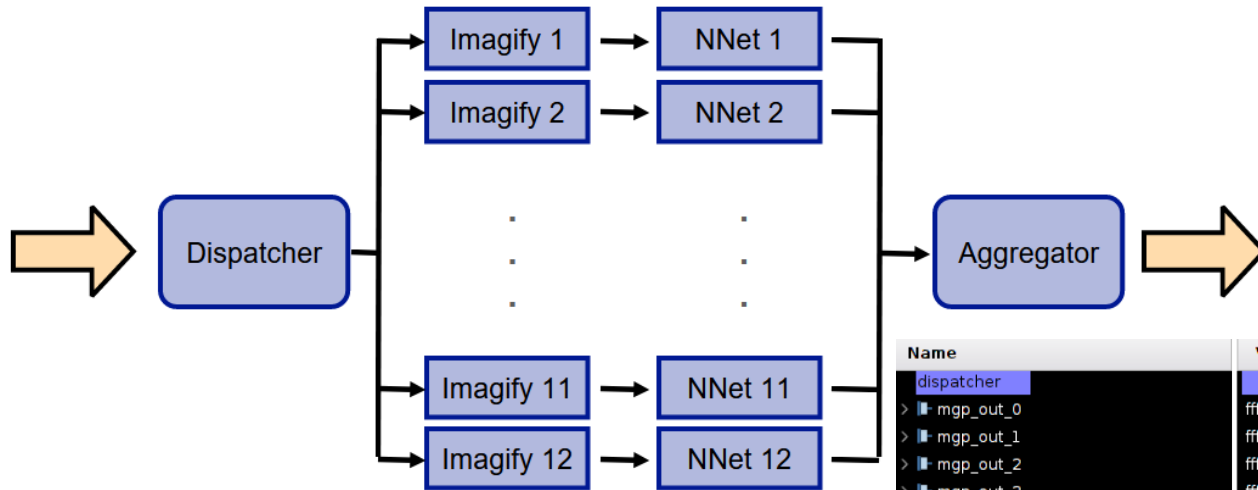


Layer (type)	Output Shape	Param #
input1 (InputLayer)	[(None, 16, 16, 1)]	0
conv1 (Conv2D)	(None, 16, 16, 8)	80
act1 (Activation)	(None, 16, 16, 8)	0
maxp1 (MaxPooling2D)	(None, 8, 8, 8)	0
conv2 (Conv2D)	(None, 8, 8, 8)	584
act2 (Activation)	(None, 8, 8, 8)	0
maxp2 (MaxPooling2D)	(None, 4, 4, 8)	0
flatten (Flatten)	(None, 128)	0
fc3 (Dense)	(None, 16)	2064
act3 (Activation)	(None, 16)	0
fc4 (Dense)	(None, 4)	68
softmax (Activation)	(None, 4)	0

Total params: 2,796

Convolutional model – Kernel replication

Throughput is not enough to sustain L0 rate, but we can replicate the network multiple times, also on multiple devices if necessary.



Resources usage for 12 replicas:

- LUT 74%
- FF 17%
- DSP 61%
- BRAM 1.4%

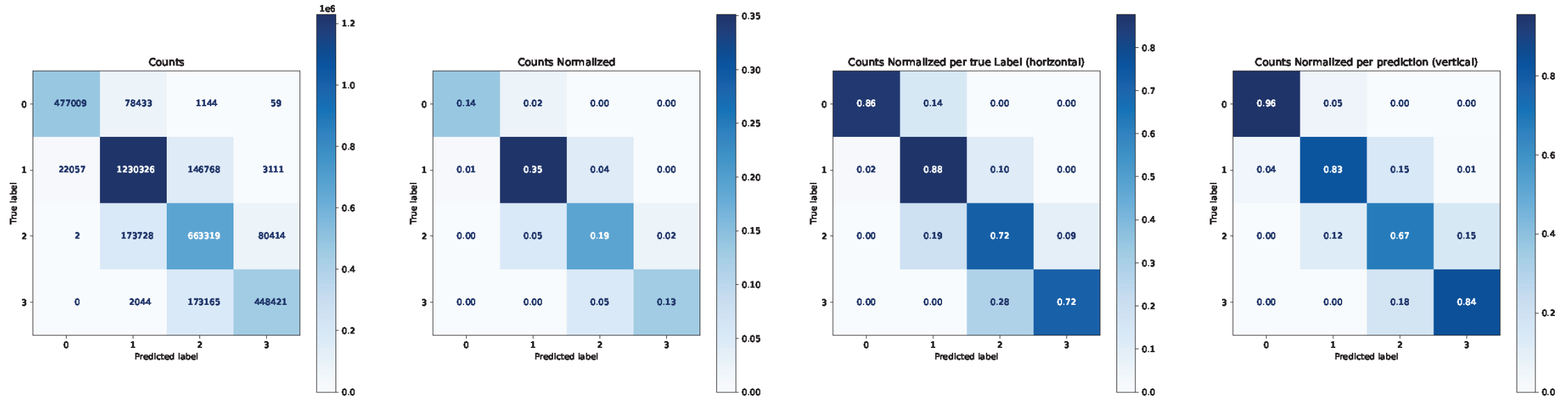
Processing time @220MHz: 137 ns
per event

Processing throughput: 7.2 MHz



Dense Model: results for classification of number of rings

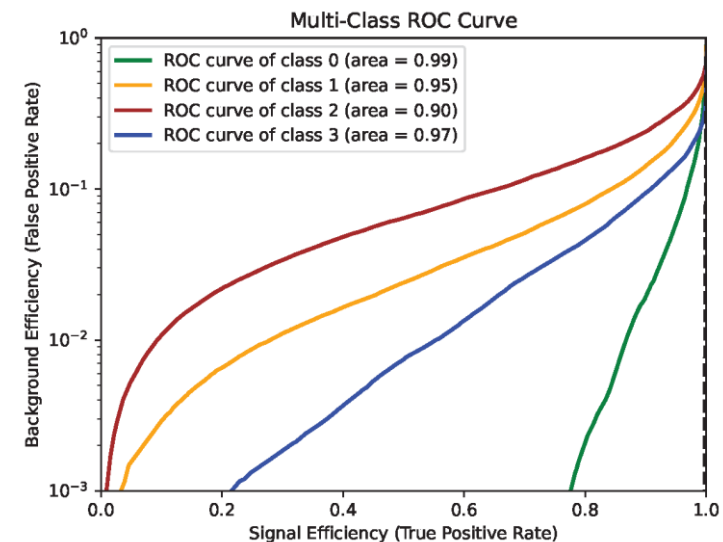
- Trained on 3 Mevents from run 8011, Validated on 3.5 Mevents from run 8893, ground truth label 1



Class 0 (0 rings) Efficiency 85.7 Purity 95.6
Class 1 (1 rings) Efficiency 87.7 Purity 82.9
Class 2 (2 rings) Efficiency 72.3 Purity 67.4
Class 3 (3+ rings) Efficiency 71.9 Purity 84.3

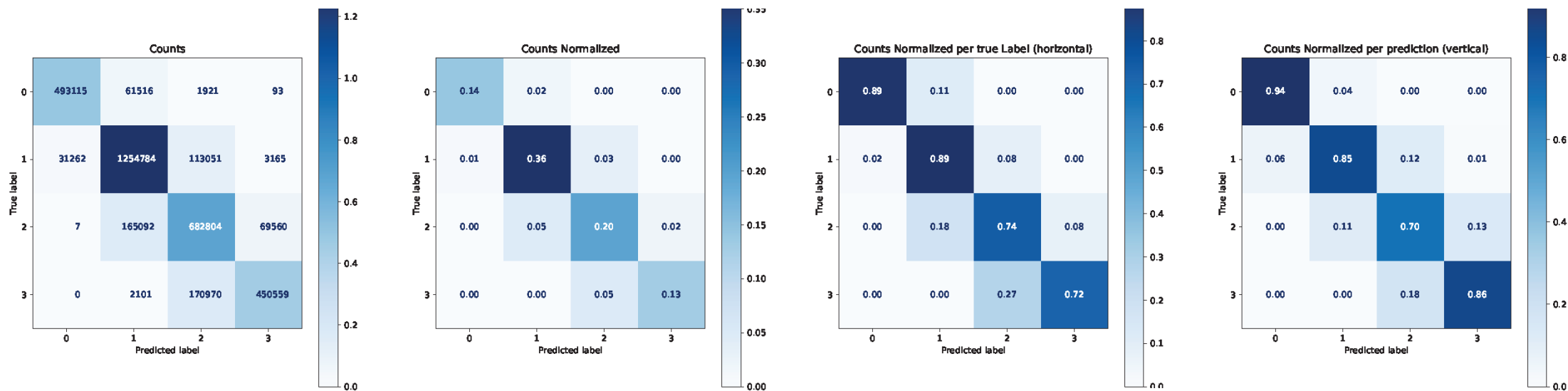
Efficiency = TP / (TP + FN)

Purity = TP / (TP + FP)



Convolutional Model: results for classification of number of rings

- Trained on 3 Mevents from run 8011, Validated on 3.5 Mevents from run 8893, ground truth label 1



Class 0 (0 rings) Efficiency 88.6 Purity 94.0
Class 1 (1 rings) Efficiency 89.5 Purity 84.6
Class 2 (2 rings) Efficiency 74.4 Purity 70.5
Class 3 (3+ rings) Efficiency 72.2 Purity 86.1

$$\text{Efficiency} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{Purity} = \text{TP} / (\text{TP} + \text{FP})$$

