



Universität
Zürich^{UZH}



Brookhaven
National Laboratory

Northwestern
University

Test-beam results for machine-learning based reconstruction of resistive silicon sensors

Don C. Wong¹

on behalf of

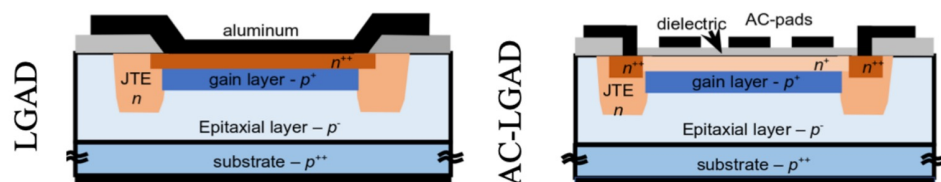
Alexander Aoki¹, Gaetano Barone¹, Leena Diehl², Marcos Fernández García³, Gabriele Giacomini⁴, Vagelis Gkougkousis², Hanshal Goyal¹, Rohan Kher¹, Daniel Li⁵, Anna Macchiolo², Yevhenii Padnuik², Daria Senina², Samantha Sunnarborg¹, Jessica Tang¹, Alessandro Tricoli⁴, and Lixing Wang¹

¹Brown University, ²University of Zurich, ³Instituto de Física de Cantabria (CSIC-UC), ⁴Brookhaven National Laboratory, ⁵Northwestern University

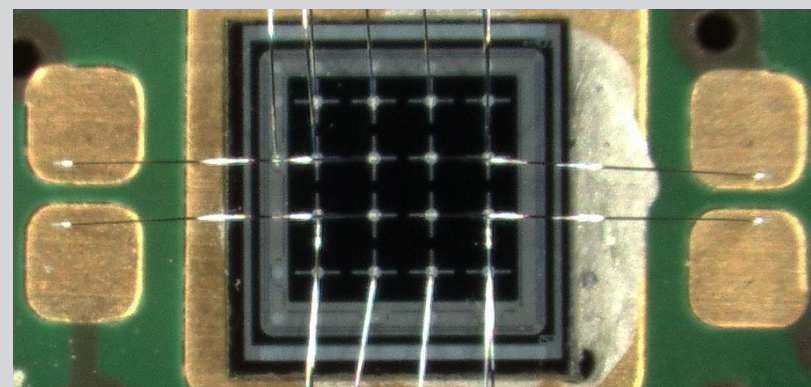


Introduction

Low-Gain Avalanche Diodes (LGADs) and AC-coupled Low Gain Avalanche Diodes



- AC-LGAD: AC pad coupled to resistive n⁺ layer through a dielectric.
 - Unsegmented gain layer → 100% fill factor + signal sharing
- Good spatial resolution with relaxed pitch: O(30) ps timing and O(10) μm spatial resolution.
- Applications: EIC, CMS tracker Phase-3 upgrade, FCC-ee. Also medical applications and future space-based particle tracking.



BNL-made AC-LGAD

Active thickness: 30 μm

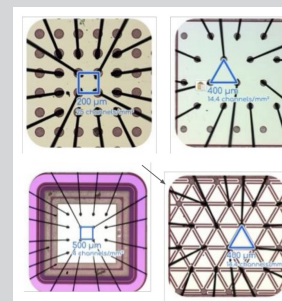
Pad size: 200 μm

Pitch: 500 μm

2x2 pads readout

$2.7 \times 10^{12} \text{ cm}^{-2}$ gain layer

Alternate geometries



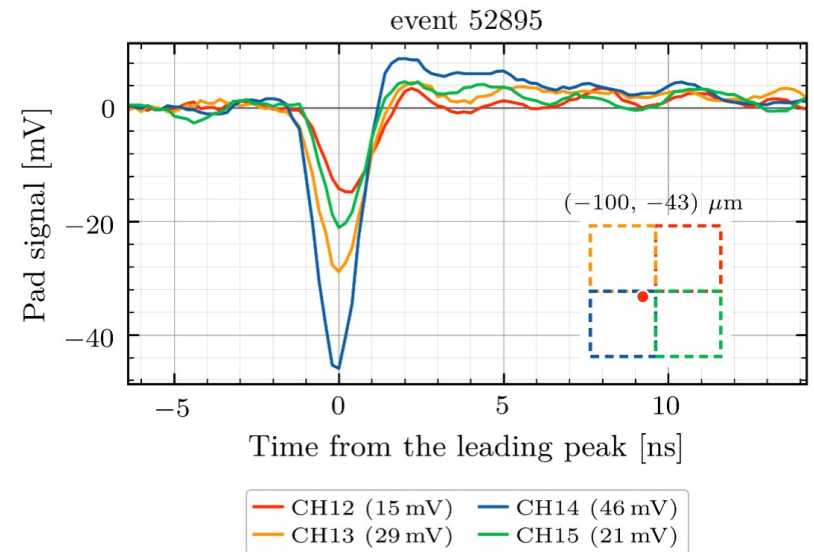
Charge Sharing

We can exploit the charge sharing property of AC-LGADs.

$$S_i = \frac{\alpha_i / \ln r_i}{\sum_i^n \alpha_i / \ln r_i}$$

- α = subtended angle (geometry-dependent) of the boundary of each electrode I, where r = distance to electrode.
- But a noise threshold usually sets a limit on information.
- Traditional methods include peak amplitudes, integrated charge, matrix inversions.
 - Computationally challenging or spatial/temporal resolution tradeoffs

We propose machine learning to extract maximal information.



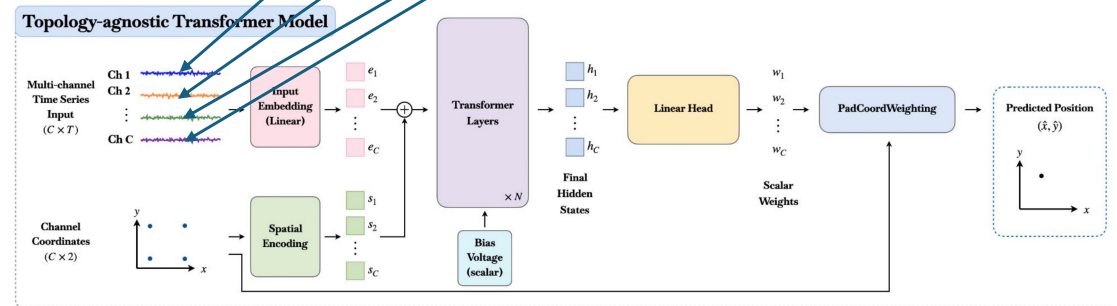
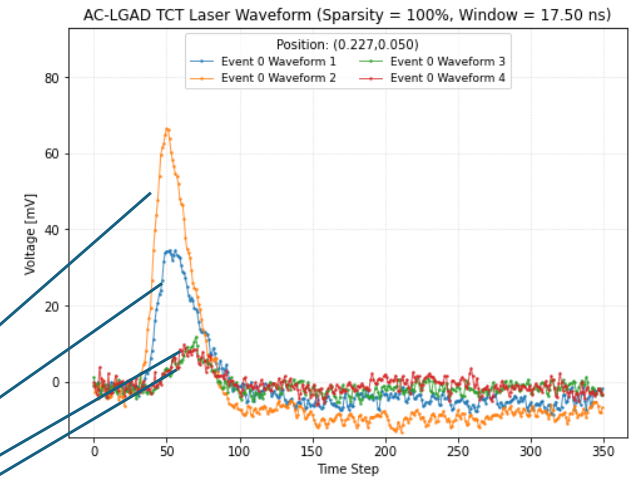
Machine Learning

We propose machine learning to extract maximal information.

- Full waveform processing to harness shape correlations between pads + pad geometry-independence = Improved position resolution!
- Challenges:
 - Landau fluctuations → Use laser-MIP test beam
 - Radiation damage → Parameterize as a function of fluences
 - Electronics limitation → Implement processing in off-detector electronics (FPGA)

Transformer-based architecture

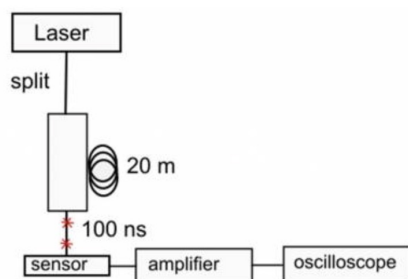
- 4 waveforms x 130 time steps → projected to 48-dimension latent vector
- CAD pad geometry
- 6-block transformer (self-attention)
- Position and uncertainty heads = final position



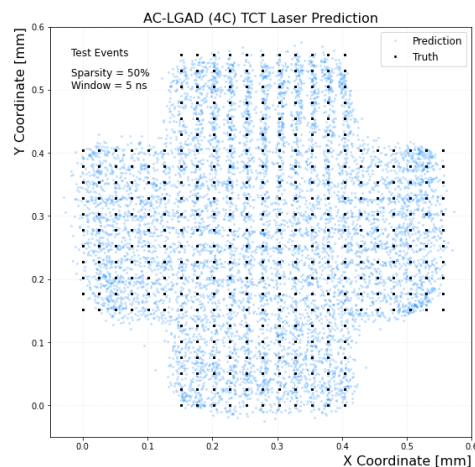
Transient Current Technique

Laser-assisted beam to simulate MIP

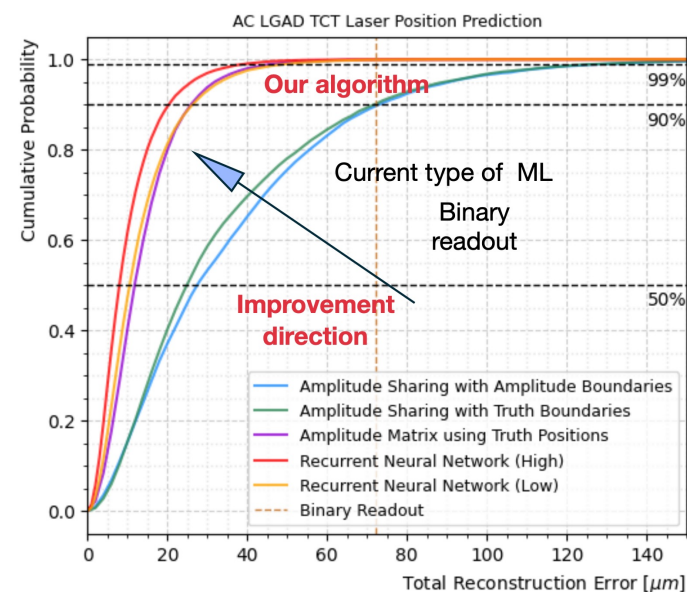
- UZH setup:
 - 385 points, $25 \times 25 \mu\text{m}^2$ spacing, 111 triggers per point
 - 1064 nm, Gaussian $\sigma \sim 9 \mu\text{m}$, $\sim 1 \mu\text{m}$ spatial resolution, two pulses separated by 100 ns
 - Bias voltage of 60, 70, 80, 90, 100, 110, 120



See Aoki et al, Machine learning-based reconstruction for resistive silicon sensors. JINST, 21(08):C08015, 2026.



With full waveform processing, we achieve a **50% improvement** over current ML methods and a **7x improvement** over binary readout.

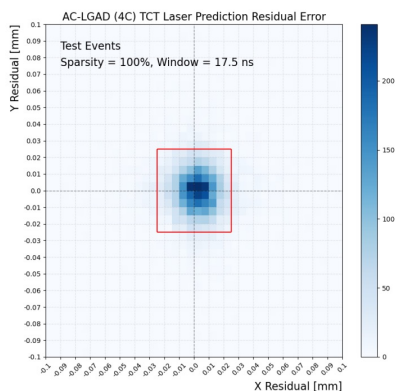


- Indicates potential resolution of $10 \mu\text{m}$ from $500 \mu\text{m} \times 500 \mu\text{m}$ pixels

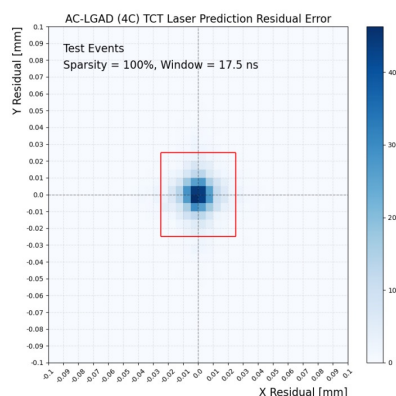
Topology-agnostic model on TCT

Transformers allow topology-agnostic learning

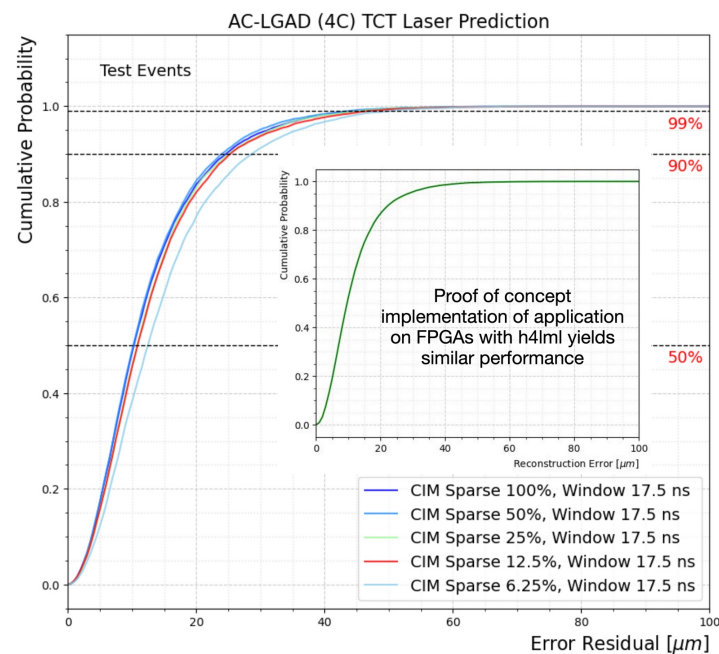
- Self-attention = readout pads as unordered set of tokens
- Can learn cross-pad correlations purely from distances and waveform features
- 10 μm on 500 μm pitch is 2% of the sensor pitch, competitive with the best results in the literature



RNN preserves
~10 μm resolution.



Transformer
reaches ~6.6 μm .

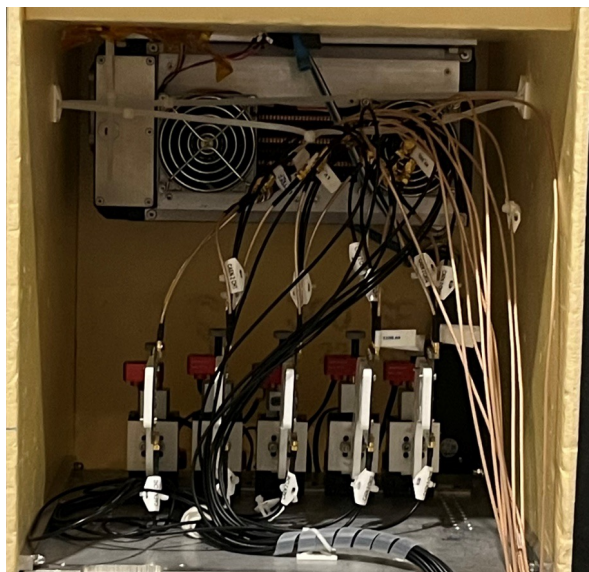


- Extremely robust to data sparsity
- No major performance drop up to 8x compression

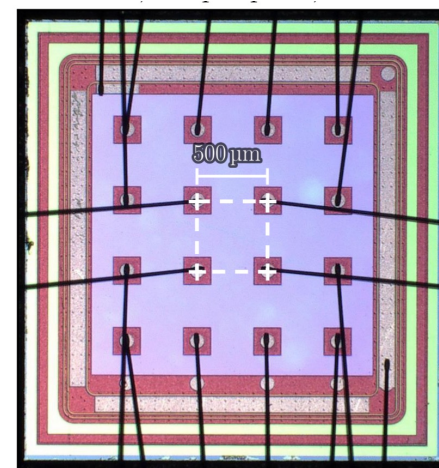
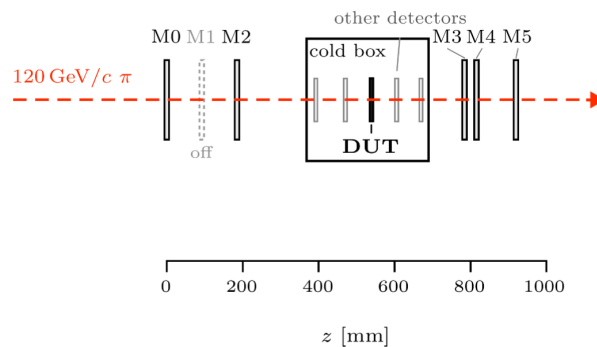
Test beam

Test beam to bypass TCT generalizations.

- TCT deposits a fixed charge at a known point
- Test beam deposits charge at unknown location → data reconstruction now becomes the constraint



- CERN SPS H6 beam, 120 GeV pions
- Chubut 2, 4 channels readout board
- Mimosa telescope
- CAEN DT5742 digitizer, 500 MHz @ 5 GS/s
- Cold box @ -12°



Test beam reconstruction

A custom reconstruction pipeline to achieve high resolution.

1. Decode and Event Sync

Parse EUDAQ2 binary. For each EventIDSyncOnline container, we write CAEN, TLU, and Mimosa events together to ensure sync.

2. Cluster and Mask

Hot pixels masked by comparing # of times pixel is hit vs # of times pixel is fired. If ratio > 50, we mask. Clustered by pixel centroid:

$$\sigma_{\text{meas}} = \frac{p}{\sqrt{12}} \approx 5.2, \mu\text{m}$$

3. Telescope pre-alignment

Millepede-II/Track χ^2 global fit of each plane's 6 DOF (x, y, z, α , β , γ) using

$$R = R_z(\gamma)R_y(\beta)R_x(\alpha)$$

4. Track fit

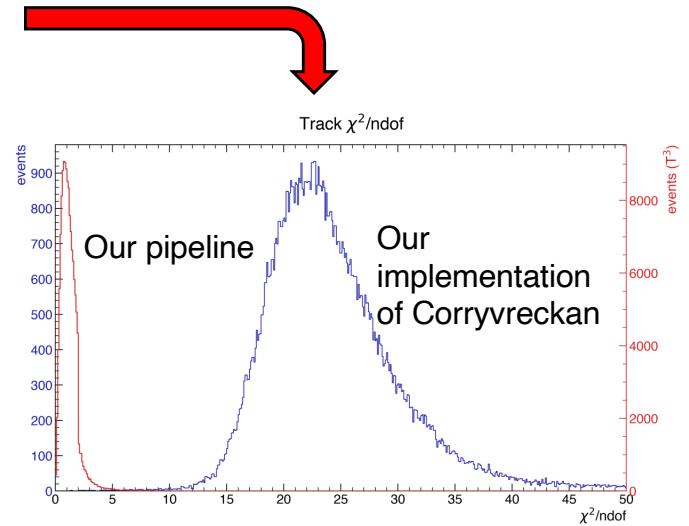
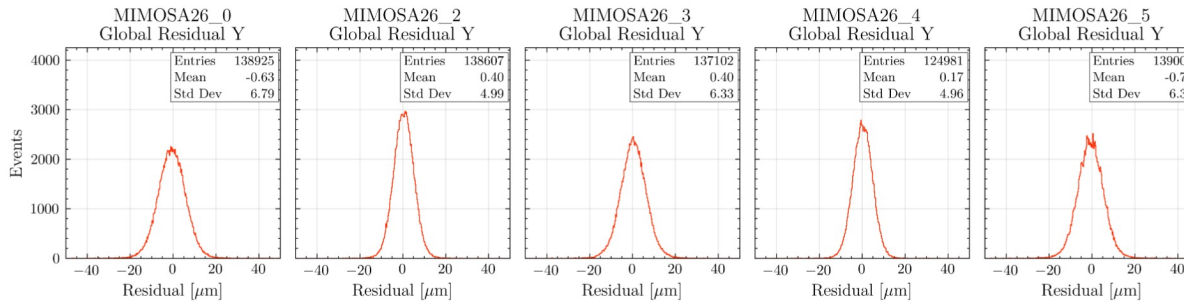
Straight-line GBL with Gaussian kink DOF at every scatterer, prior from Highland formula.

5. DUT alignment and tracks

SNR-gated charge-weighted centroid + eta correction + CFD50 timing with time-walk correction. Tracks extracted with iterations of closed-form 2D Kabsch SVD.

6. Machine Learning

CIM + Transformer encoder. Takes full 1024-sample waveform and 12 features (peak amplitude, charge fraction, etc) to learn position and timing information.



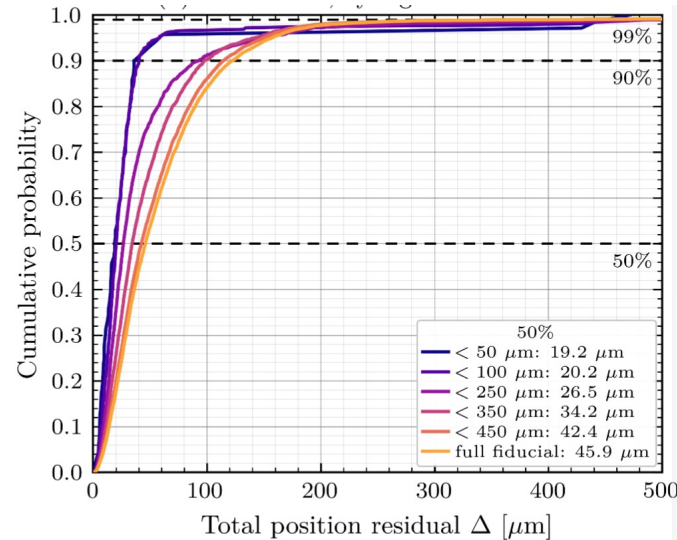
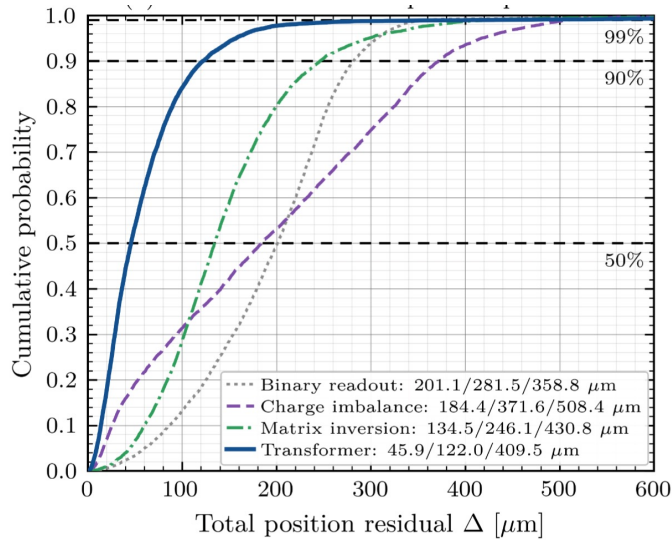
○ Achieved χ^2 of 1.02 vs. 24.25

Topology-agnostic model on TB

Maintained competitive resolution after custom reconstruction.

$$\hat{x} = k \frac{Q_R - Q_L}{Q_R + Q_L}, \quad \hat{y} = k \frac{Q_T - Q_B}{Q_T + Q_B},$$

- At full fiducial, we beat charge imbalance and matrix inversion methods by $\sim 3\times$.
- 17.6 μm on 500 μm pitch is 3.5% of the sensor pitch, competitive with the best results in the literature
- Current results limited by statistics and lower bias voltage



Temporal studies and limitations

Transformer model uses time evolution to improve resolution

- Typically assume waveform peak is centered in a fixed time window
- In test beams, pulse arrival fluctuates (time-jitter)

Model and training	r_{50} In-hull		r_{50} Full ROI	
	190 V	100 V	190 V	100 V
GeoRead, no augmentation	4.18 (5.38)	5.80 (6.39)	6.28 (7.65)	9.74 (10.66)
Full-waveform, no augmentation	3.29 (4.90)	5.29 (6.47)	5.31 (9.49)	9.07 (11.94)

- Topology agnostic: +1.37 μm
- Full-waveform: +4.18 μm

Validate “topology-agnosticity” with different geometries.

- Reconstruction with triangular pad patterns



Conclusions

We applied frontier ML architectures on TCT and test beam data, yielding

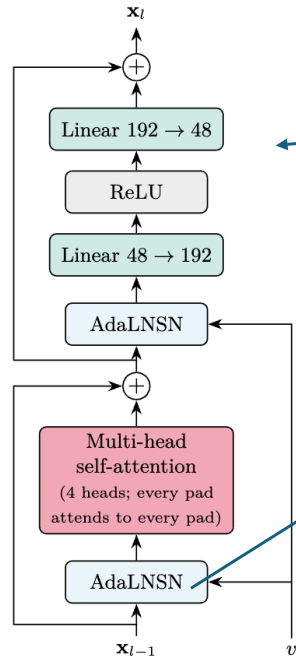
- TCT → beat traditional methods by $\sim 7\times$ and 2% of pitch is competitive
- ML → topology-agnostic model extremely robust to data compression
- Test beam reconstruction → custom pipeline achieved high accuracy (Corryvreckan)
- Test beam → beat traditional methods by $\sim 3\times$ and 3.5% of pitch is competitive with literature
- Current results limited by statistics and lower bias voltage

Several open questions are to be investigated.

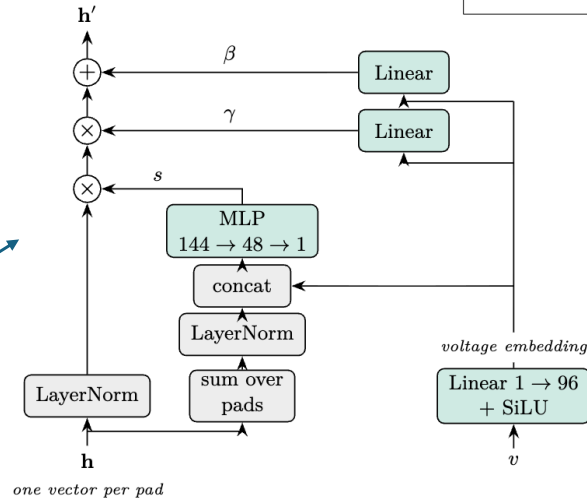
- Geometry dependence → validate topology-agnostic model
- Irradiation campaign with Ljubljana to test post-irradiation performance
- More statistics for test beam runs
- Reconstruction pipeline to be published soon: we welcome collaborators and other teams to try!
- Future test beams: we would love to collaborate!
gaetano_barone@brown.edu or
don_wong@brown.edu

Additional material

Backup



(b) Transformer block



(c) AdaLNSN: voltage-conditioned normalisation

