Hit position reconstruction with Resistive Silicon Detectors using Machine Learning techniques

16th Topical Seminar on Innovative Particle and Radiation Detectors

28.9.2023

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Outline

- Resistive Silicon Detectors (RSDs)
  - FBK RSD2 production
- Position reconstruction with Machine Learning techniques
- The RSD2 “cross 450 um”
- Results
  - Training with laser
  - Test beam results
  - Comparison

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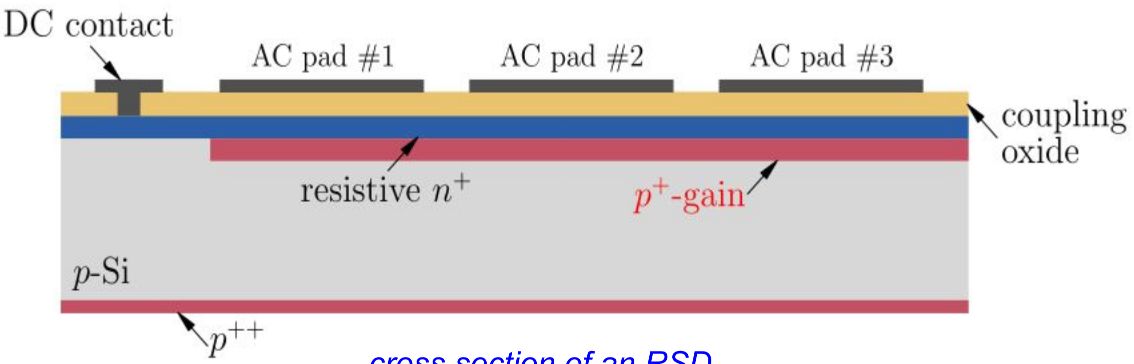
Resistive Silicon Detectors (RSDs, aka AC-LGAD)

- Silicon sensors based on the **LGAD technology**, implementing **AC-coupled resistive read-out:**
  - **Metal read-out pads** coupled to the sensor through an **oxide layer**
  - **Resistive n$^+$ electrode** allowing sharing of charge among multiple read-out channels
  - **Continuous gain layer** spreading across the active area

~ 50 µm active thickness



cross section of an RSD

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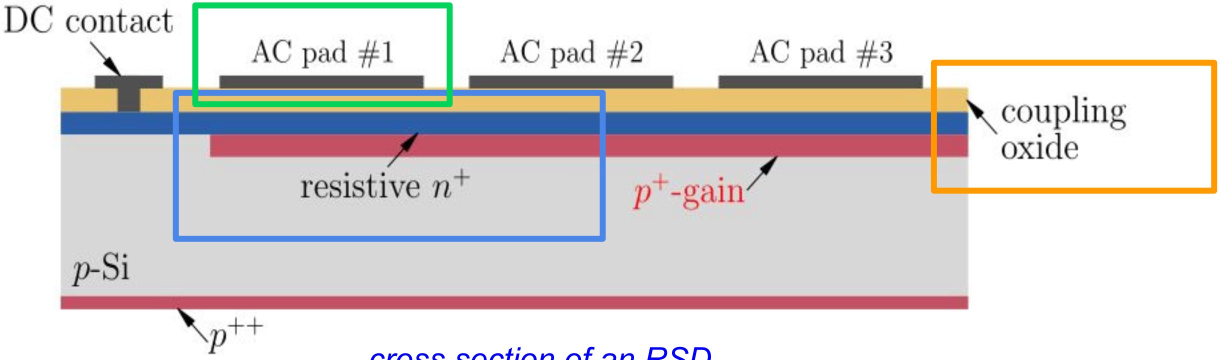

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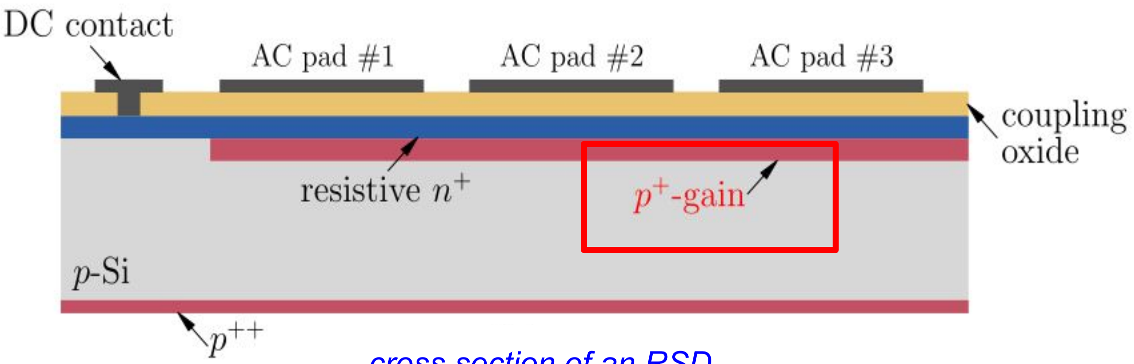

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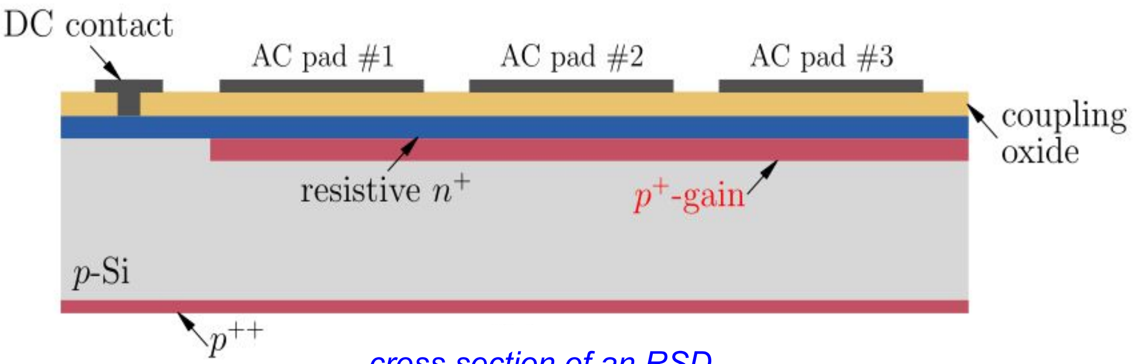

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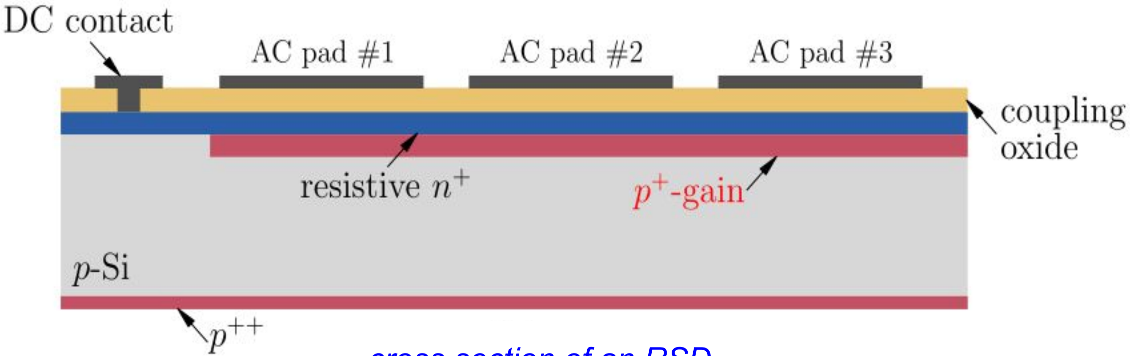
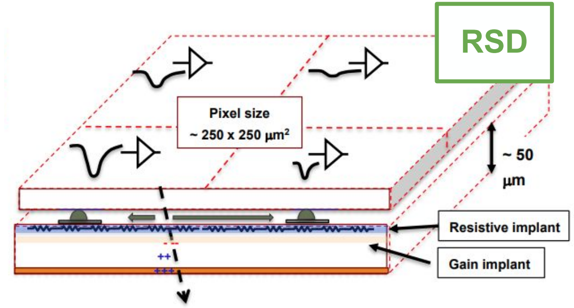
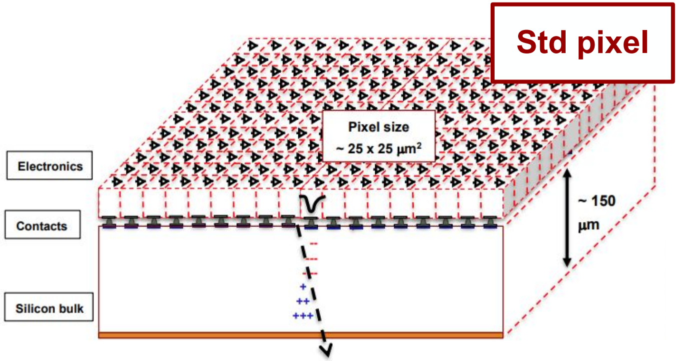


cross section of an RSD

What do we need RSDs for?

- The RSD “recipe”: combine multiple read-out channels to achieve accurate reconstruction of the hit position
    - **RSD spatial resolution: $\sigma_{RSD} \geq 0.03\cdot$pitch** (link)
    - Traditional pixel sensor with binary read-out: $\sigma_{Pixel} \geq 0.15\cdot$pitch*
    - RSD needs fewer read-out channels to achieve same σ





Lower limit in presence of a magnetic field, in general σ_{Pixel} ~ 0.30·pitch

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  - **30-40 ps time resolution** (link)
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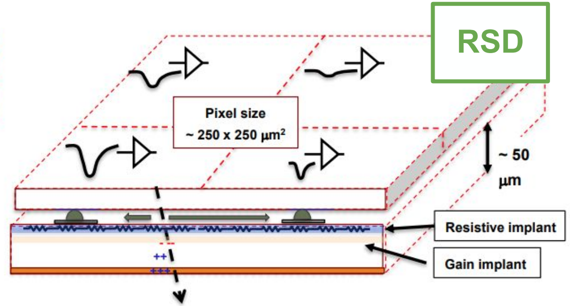

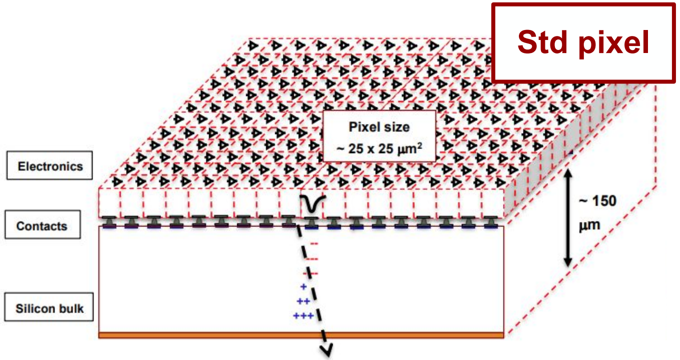

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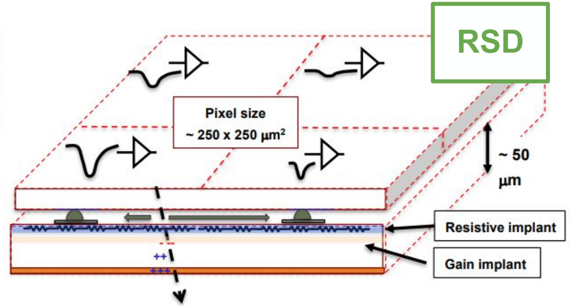
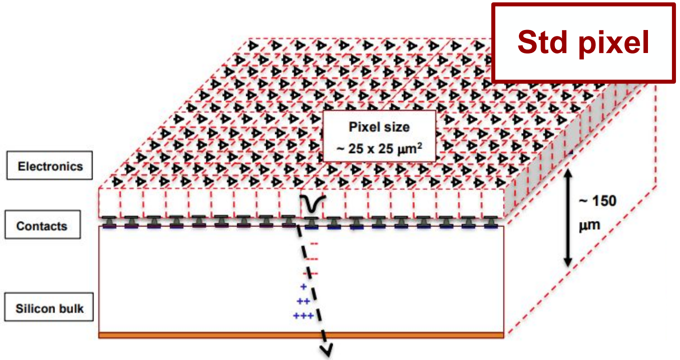
- **100% fill factor by design**





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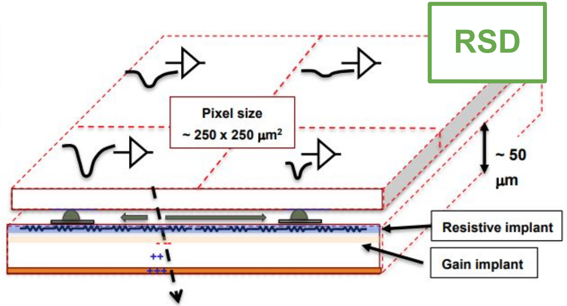
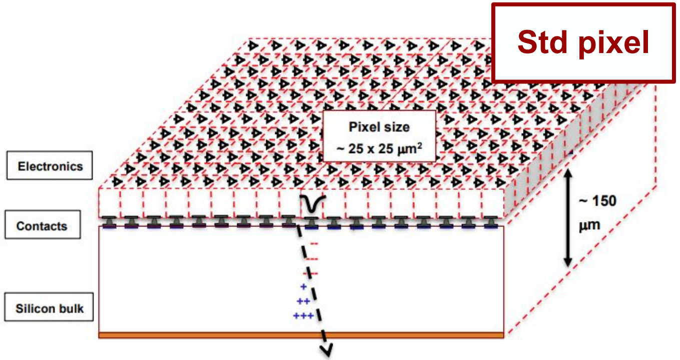
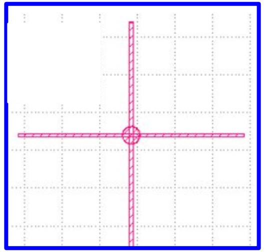


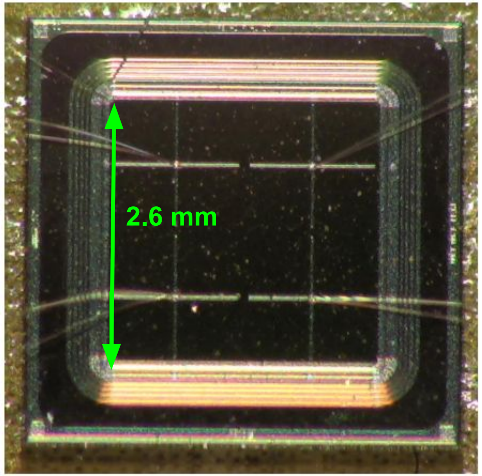


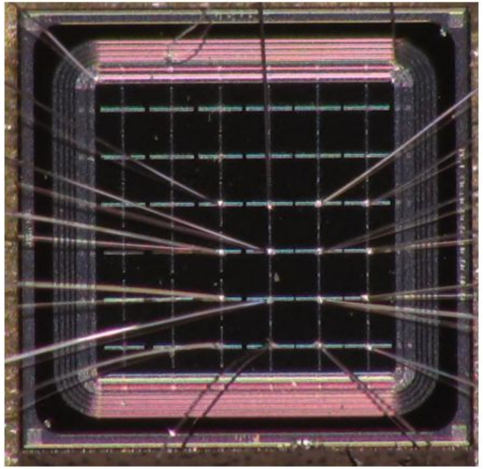
→ RSDs are suited as 4D-trackers for future experiments

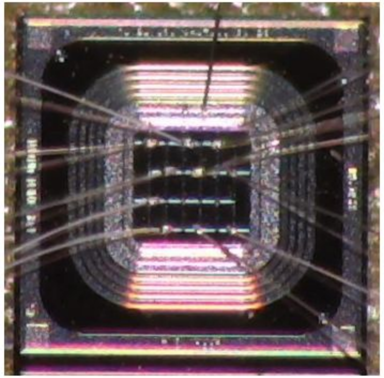
The FBK RSD2 production

- The sensors presented in this work come from the second RSD production manufactured by Fondazione Bruno Kessler (FBK, Italy), RSD2
- **RSD2** introduces the innovative **cross-shaped layout of the metal pads**
  - cross-shaped electrodes minimize the area covered by metal, enhancing signal sharing, as in RSD there is no sharing underneath metal









***RSD2 sensors**: more details here*

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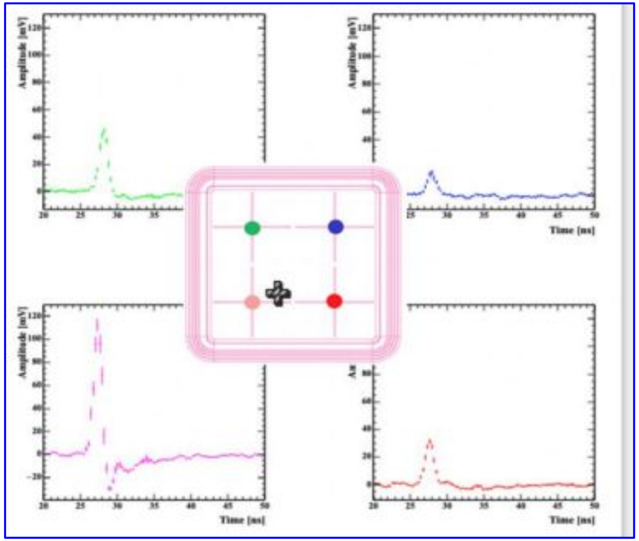
A glance at how these sensors work in a 4-electrodes version

- When a particle hits the sensor (position of the cross), all 4 neighbouring pads see a signal, with amplitude depending upon their relative distance from the hit position
- Those signals carry valuable information that can be used to reconstruct the hit position



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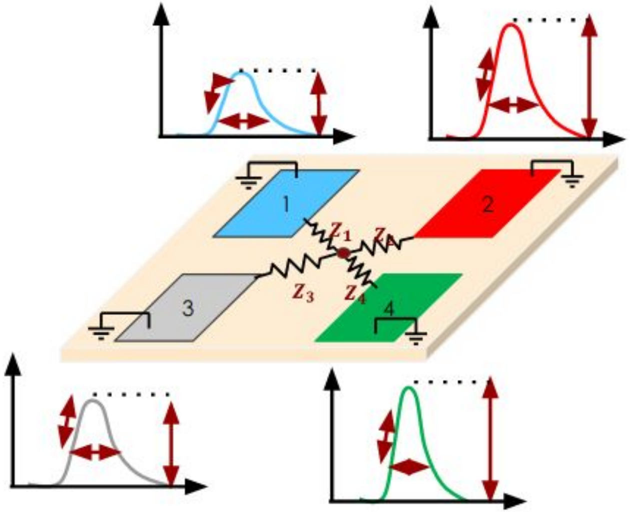
Machine Learning applied to RSD

- Position reconstruction in RSD is rather straightforward
  - Extract signal characteristics from each read-out channel
  - Provide 2 outputs (the x-y coordinates of the particle hit position)



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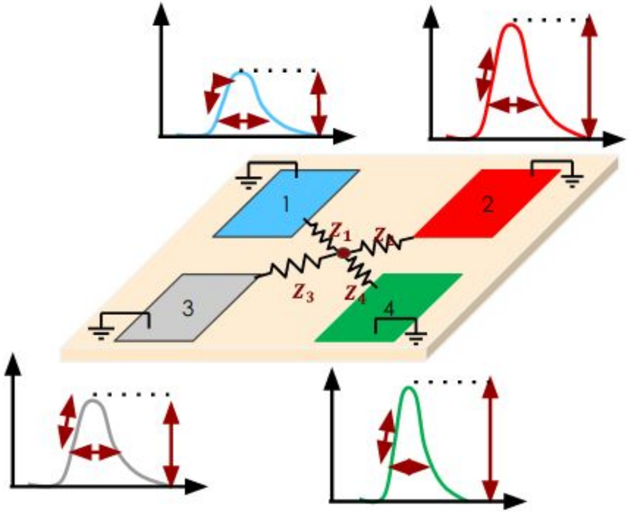
- **Analytical models can infer the hit position using the signal characteristics**
  - see the *charge asymmetry* method
  - work well in the simplest case with only 4 read-out channels, less accurate in the more realistic scenario where many pads are used



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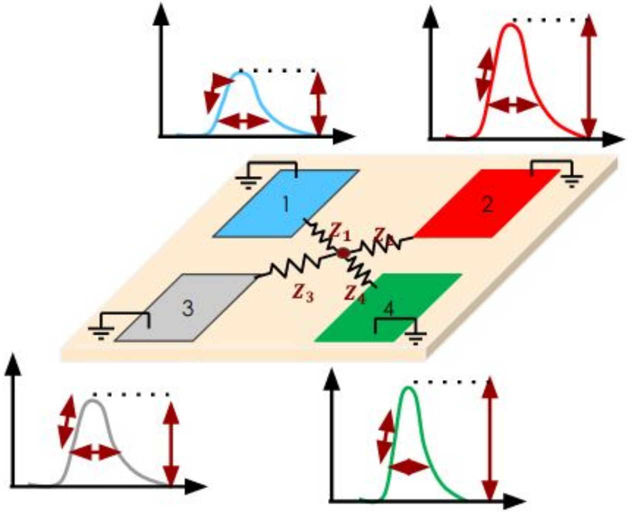
- **Machine learning algorithms are a natural alternative choice:**
  - Train the algorithm with signal characteristics as input features
  - Predict the particle impact position once the algorithm is trained
  - In principle, the larger the number of pads used, the more accurate the prediction

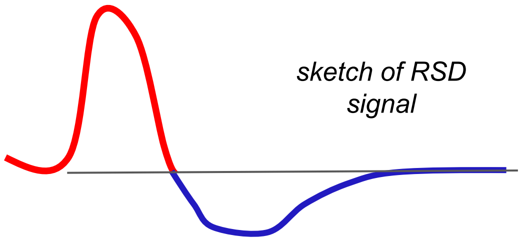


Machine Learning algorithm

x-y coordinates of impact position

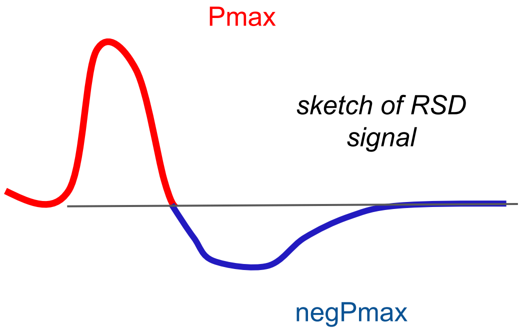
The machine learning approach

- We used amplitudes of positive and negative lobes (RSD signals are bipolar) of all read-out pads as input features



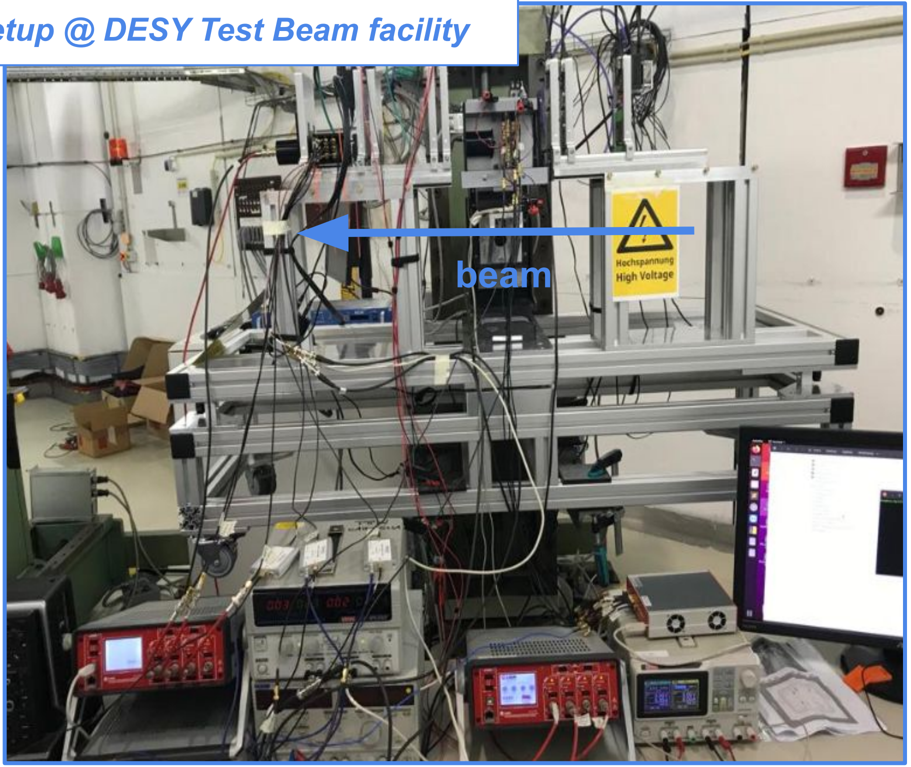
The machine learning approach

- We used amplitudes of positive and negative lobes (RSD signals are bipolar) of all read-out pads as input features
- The **model has been trained with laboratory data**, taken with a precise TCT setup
    - IR laser simulates the passage of a ionizing particle
    - An x-y stage provides the laser reference position with ~2 um resolution
- The **test dataset**, instead, has been acquired at the **DESY Test Beam Facility**
    - 4 GeV electrons beam
    - Facility equipped with EUDET-type pixel beam telescopes with estimated ~ 15 um spatial resolution (can go down to 2 um in ideal conditions)

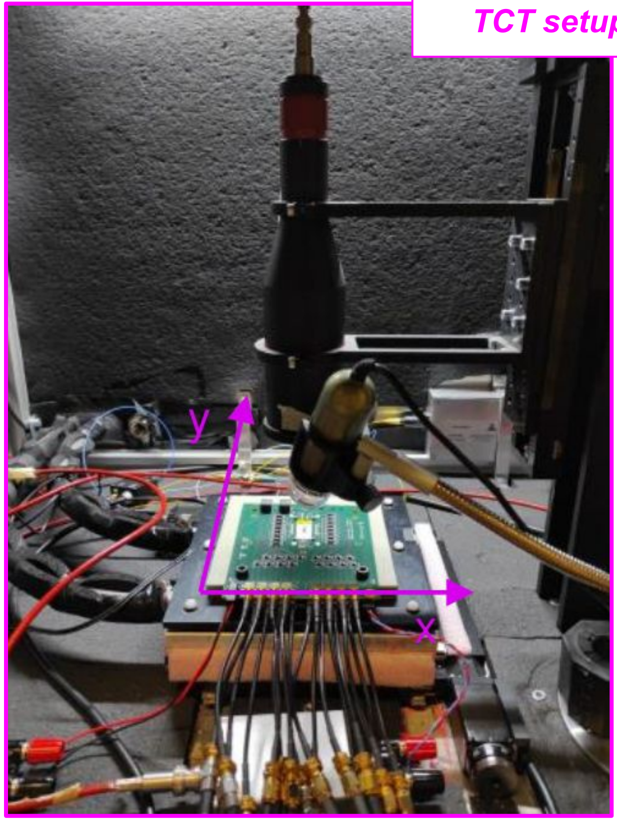


The machine learning approach

Setup @ DESY Test Beam facility



TCT setup



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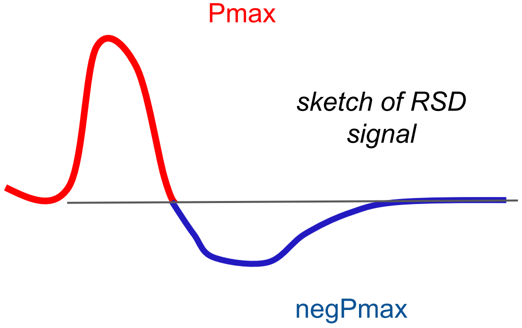

Why training with laser data?

- Lab datasets may have millions of events, in TB are limited (by now) to ~100k
- Lab data are taken in ideal conditions: uncertainty on reference positions ~2um vs 15um of tracker
- Train the model in the lab, then use it to make predictions in different conditions → a way to prove the generalization power of the model

The machine learning approach - 2

- The chosen model is a **fully-connected dense neural network**
  - 6 hidden layers, with 36 nodes each
  - *Tanh* as activation function, *Adam* as optimizer

- In this work we developed our model using *pyTorch*:
  - flexible and tunable, can be easily adapted to our needs
  - Dropout layer to mitigate overfitting
  - Regularization layer (reduce the importance of outliers and result in a more symmetric distribution of predicted positions)
  - Use an adaptive learning rate (the parameter controlling "how fast" the model learns) to better pinpoint the local minima of the loss function

→ thanks to this updated model, fine tuned on our needs,
the results improved by almost 20% wrt previous results

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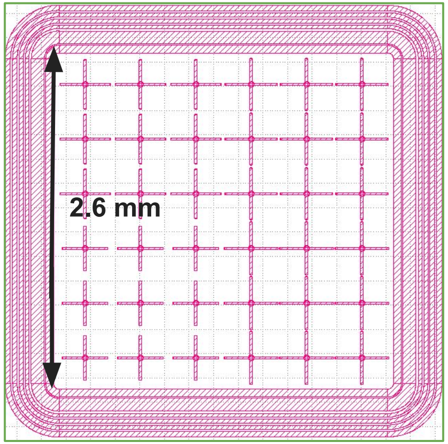
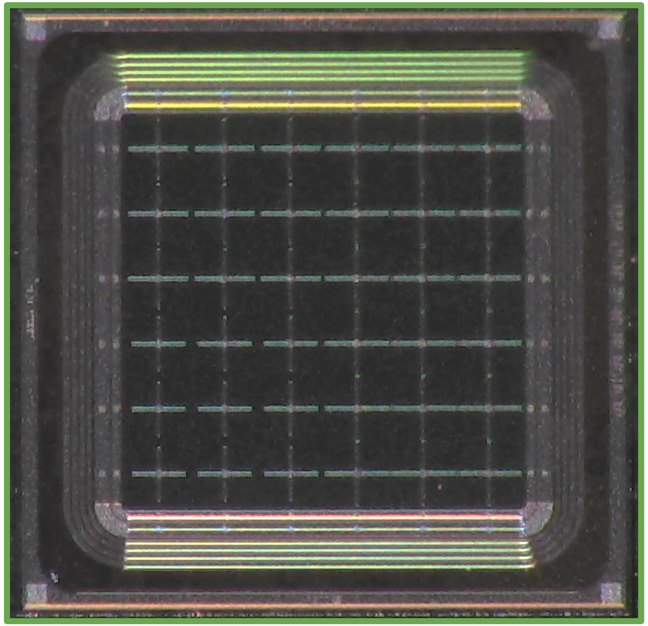
The RSD2 “cross” 450 um design



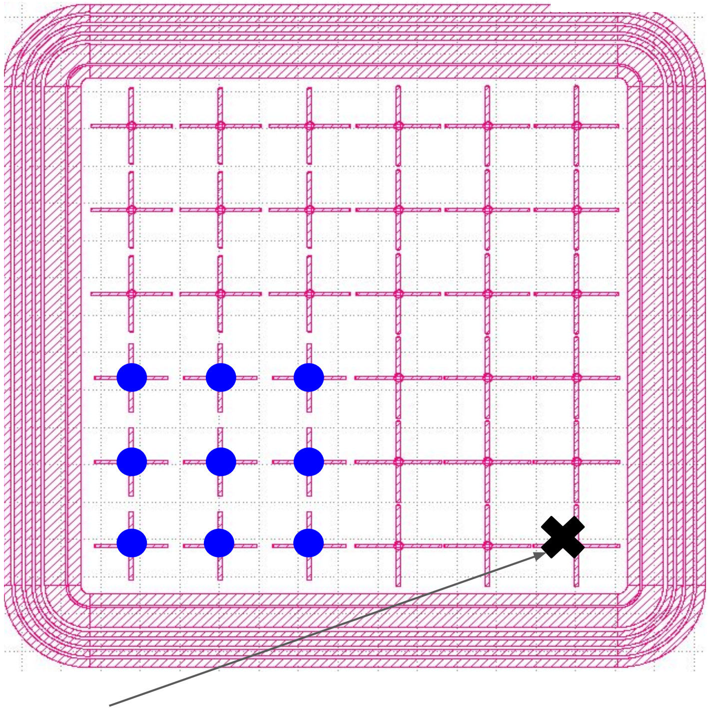


The device under test in this study is an RSD2 6x6 pixel sensor

- cross-shaped electrodes
- 55 um active thickness
- 2.6 x 2.6 mm^2 area
- 450 um pitch
- Operated at gain ~ 10

The RSD2 “cross” 450 um design

- 9 pads read out from DUT (3x3 matrix)
- Position reconstruction in RSD works using the pads that see a signal above the noise level (i.e. the closest to the hit position)



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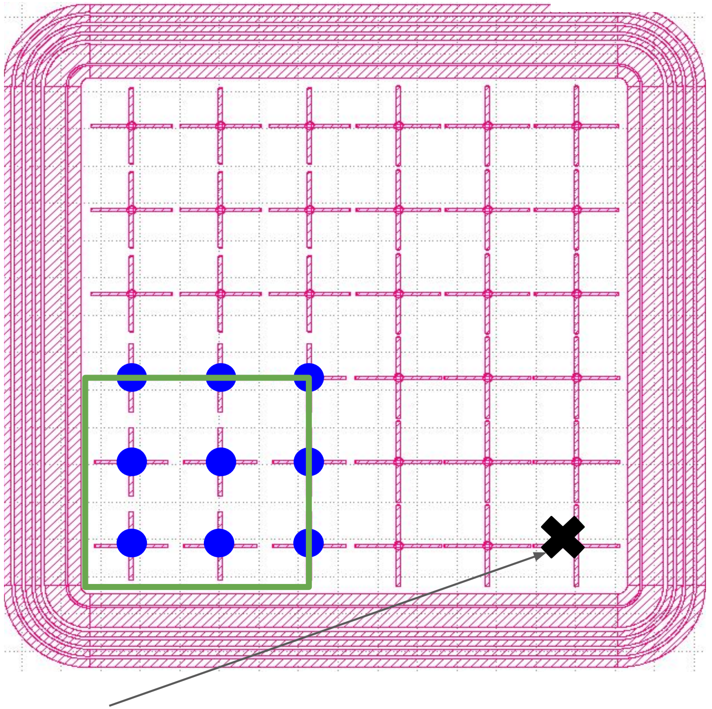

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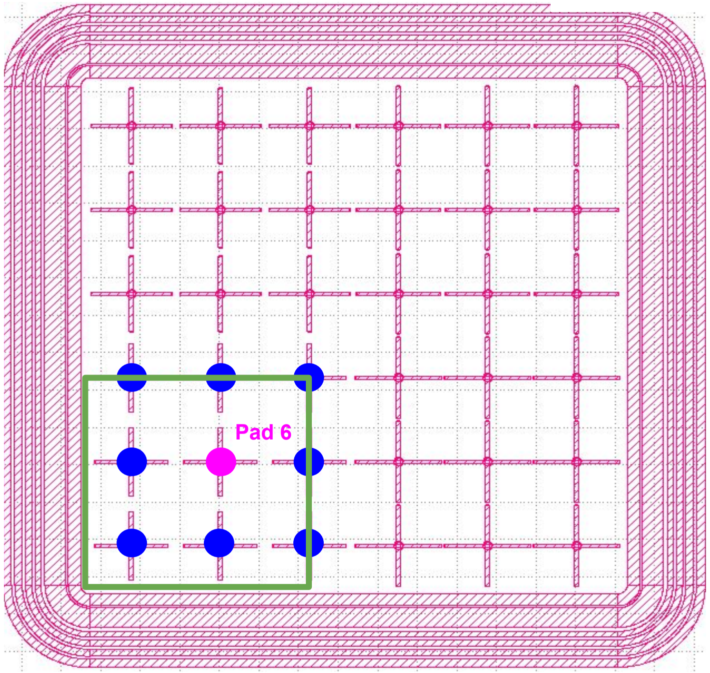
  - Pad 6 signal amplitude > 5 mV (cut most noise events)
  - Pad 6 sees the highest signal among all pads



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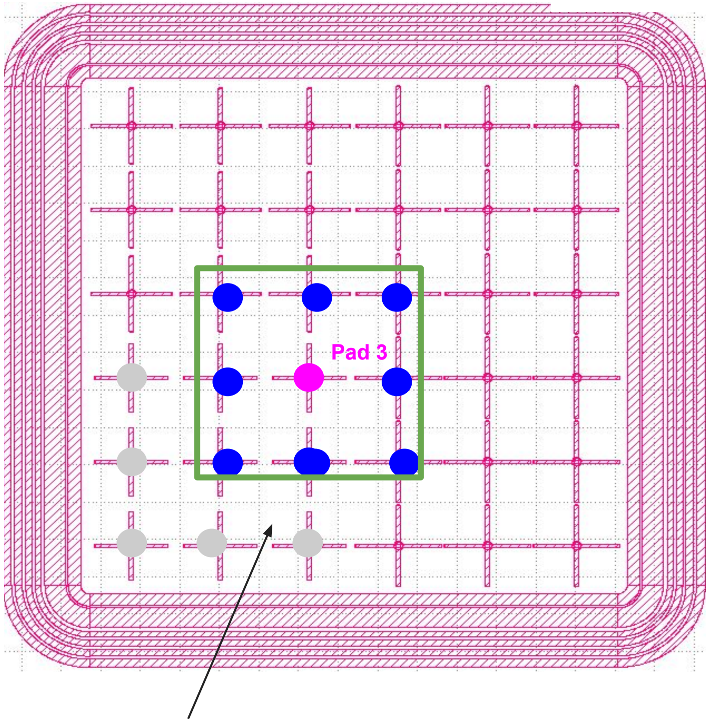

If Pad 3, instead of Pad 6, sees the highest signal, we should use a different 3x3 matrix

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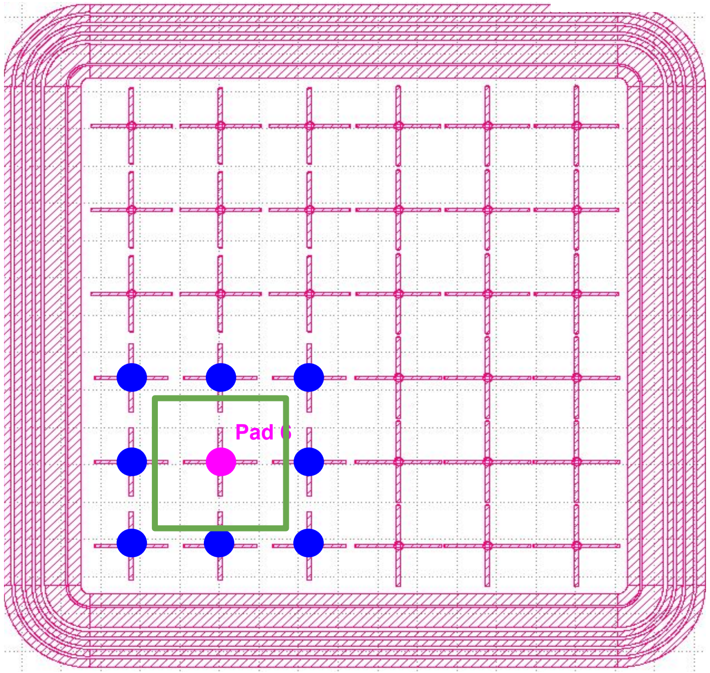

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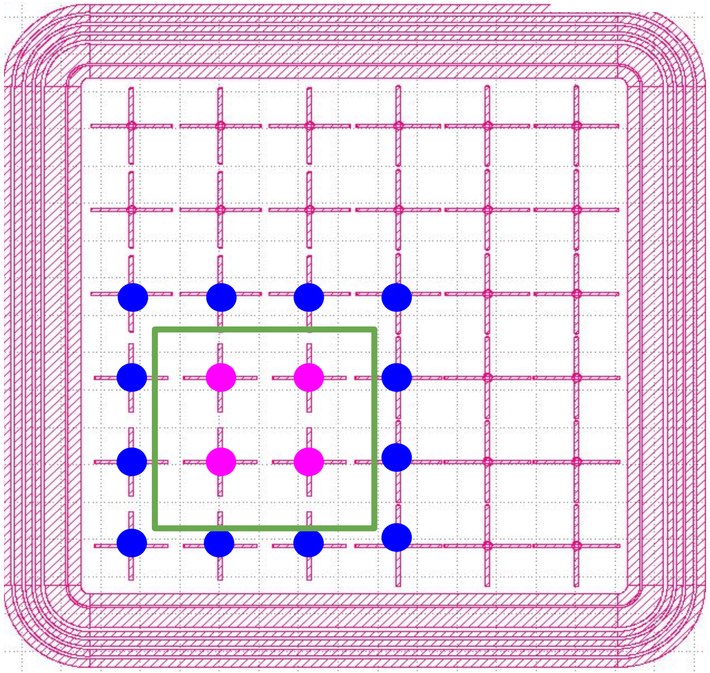

4x larger ROI by using 16 pads

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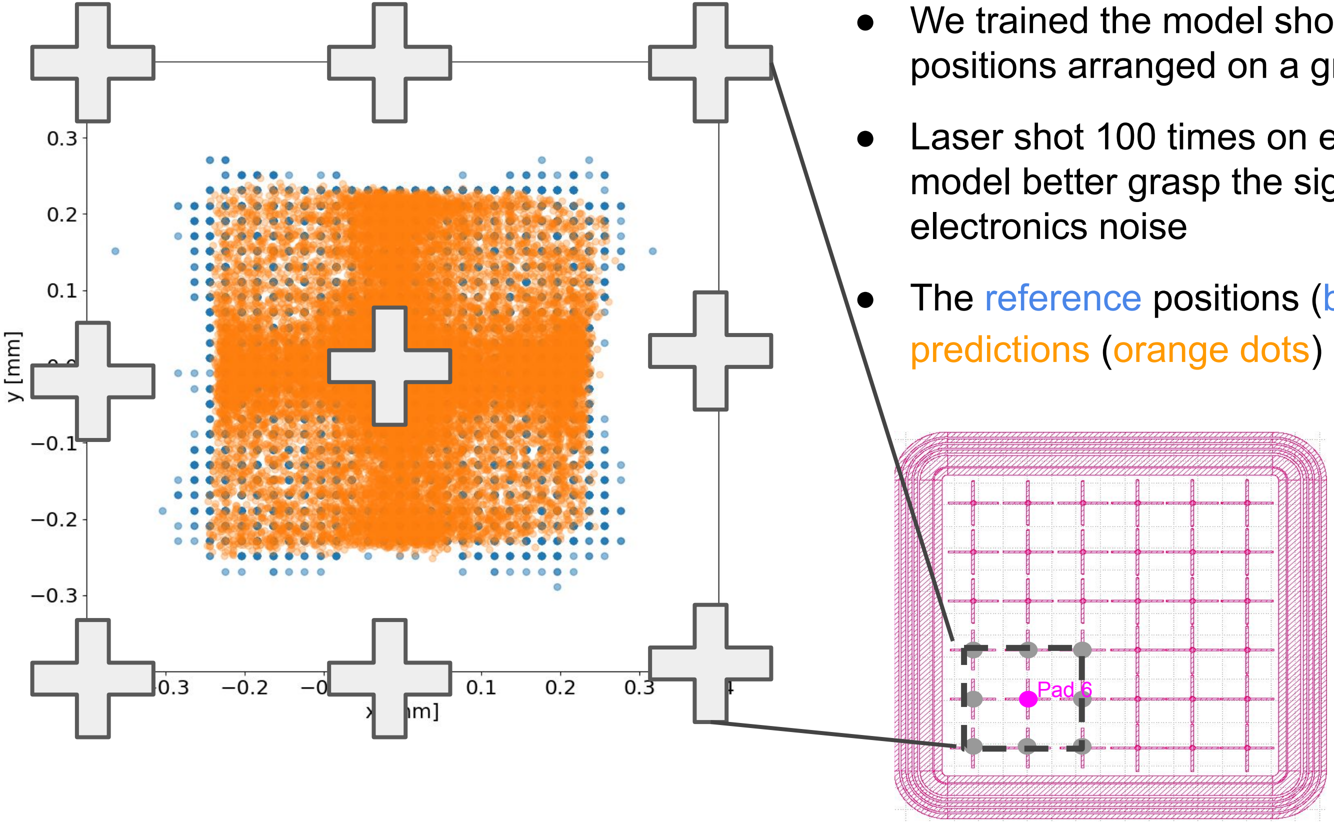
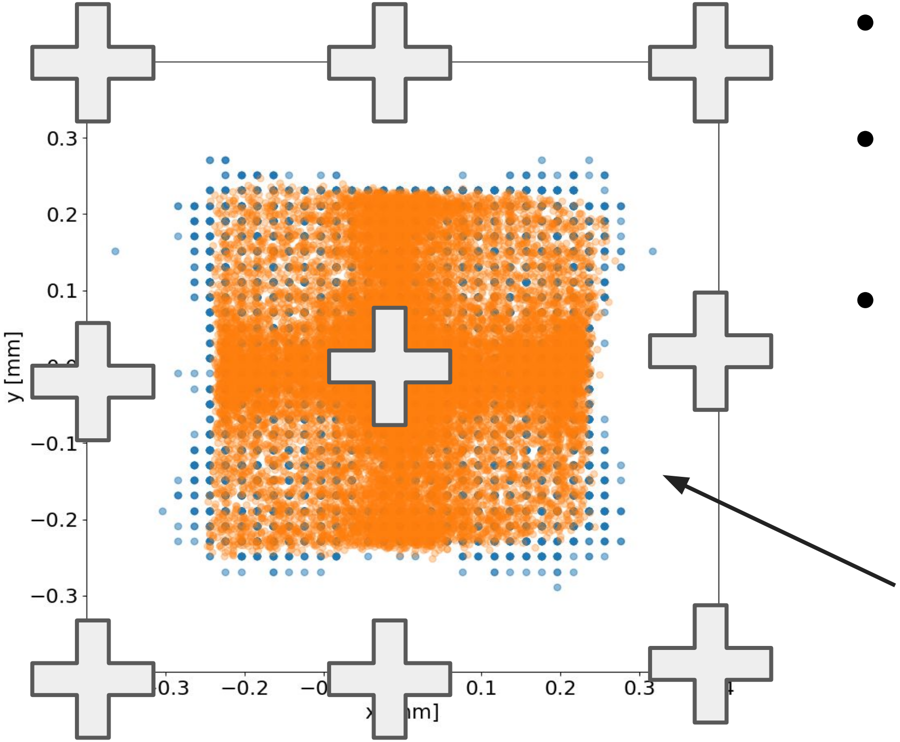


- We trained the model shooting the laser on different positions arranged on a grid within the ROI
- Laser shot 100 times on each grid position, to let the model better grasp the signal fluctuations due to the electronics noise
- The reference positions (blue dots) are then compared to predictions (orange dots) after the model is trained

Training the Neural Network



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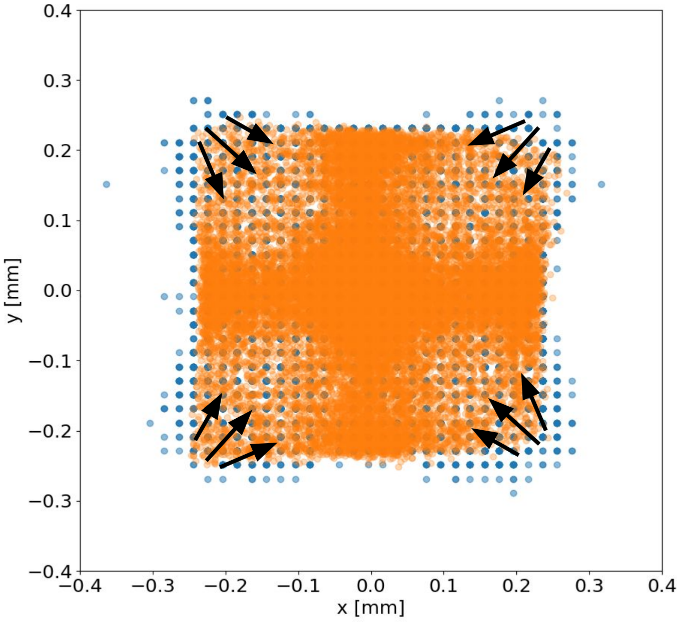
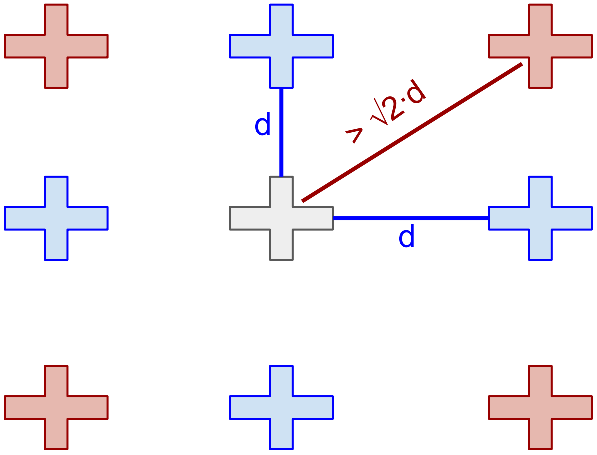
Predictions are not arranged on a grid as the reference positions, why?

Training the Neural Network - 2

- If the design is based on squares, the pads in the corners (given the requirements previously mentioned) see a smaller signal than the others
- As a consequence, they are "less important" in the reconstruction, and predicted positions tend to be "pulled" towards the center by those pads seeing higher signals





The pattern reflects the pad geometry…

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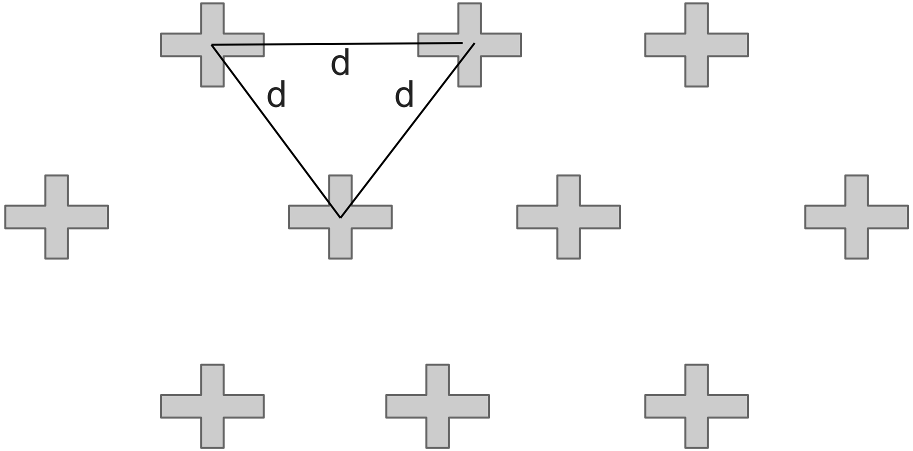
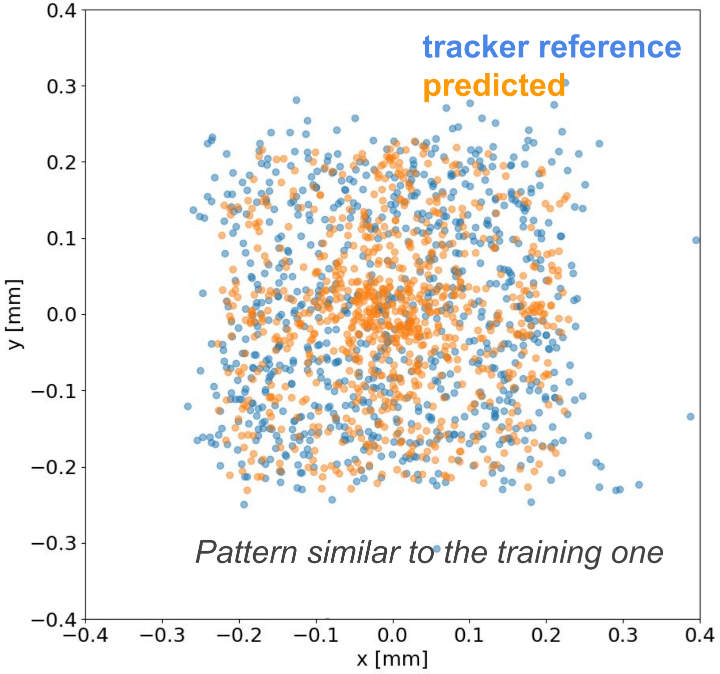
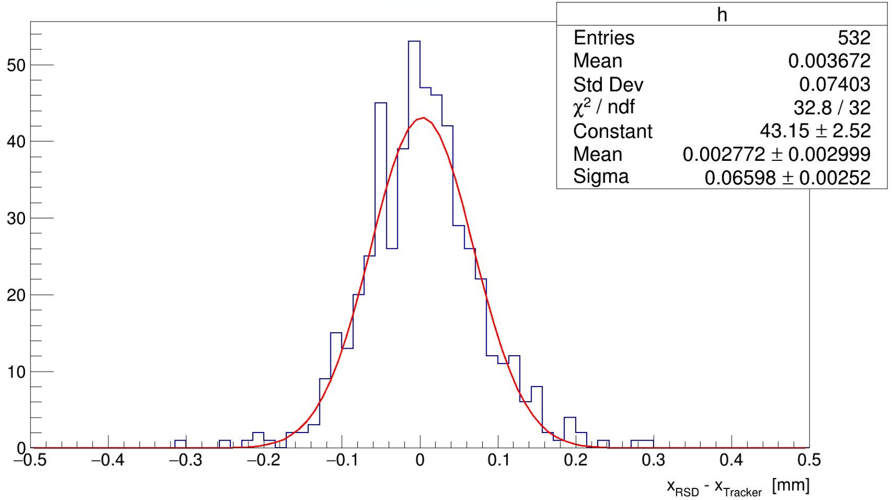
We plan to fix this issue by introducing new pad designs based, for instance, on triangles, so that all pads are equidistant



Results from the DESY TB

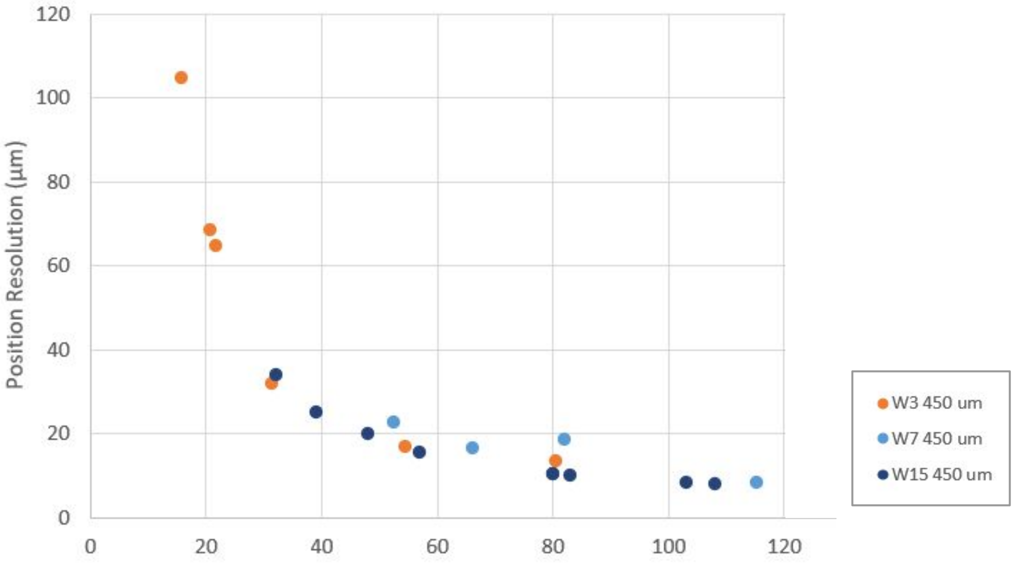
- We used the model trained with laser data to predict the DESY test beam positions
- Sensor, temperature, gain level and read-out chain are the same as laboratory tests
- The sensor achieved $\boldsymbol{\sigma_{RSD}}$ **~ 65 um**





Comparison with laboratory tests

Summary of RSD2 cross 450 um resolution measured in the lab, using the TCT setup



Sum of the 4 highest amplitudes in the matrix [mV]

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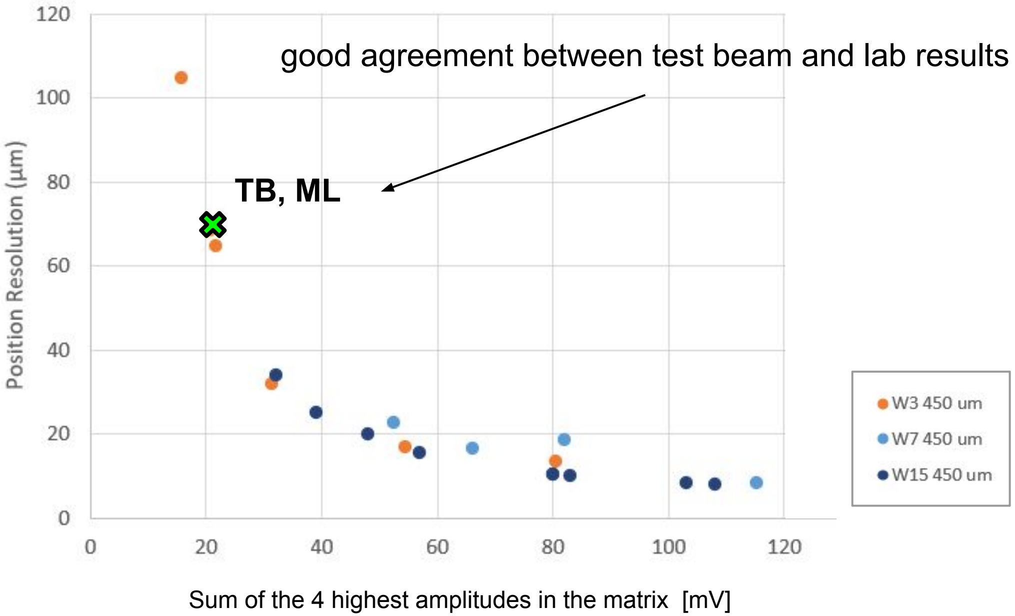

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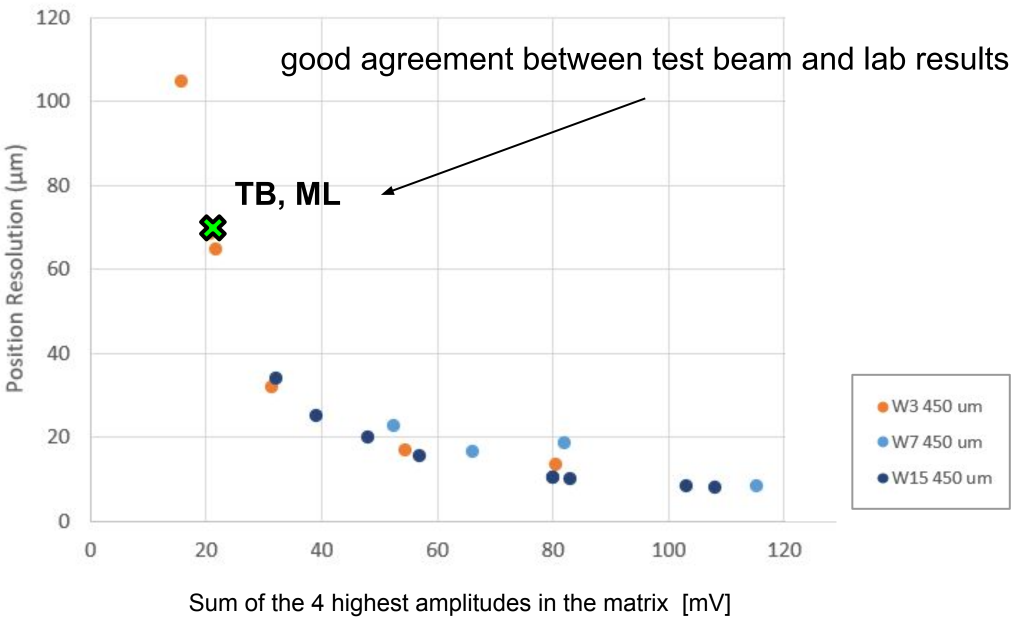

By increasing signals,
σ_{RSD} can significantly drop

→ low signals at the TB due to a read-out board not suited for RSDs

Summary

- Resistive Silicon Detectors (RSDs) are innovative LGAD silicon sensors with 100% fill-factor, implementing the AC-coupled resistive read-out
- **RSDs are suited as 4D-trackers for future experiments, able to provide picosecond-level time resolution and micron-level spatial resolution**
  - Position reconstruction is enhanced in RSD by using machine learning techniques
  - In particular, ML gives accurate predictions when using many pads in the reconstruction
- The sensor presented in this work comes from the FBK RSD2 production and features a pitch of 450 um
  - It has been **measured during a DESY test beam**, achieving $\boldsymbol{\sigma_{RSD}}$ **~ 65 um**
  - This is a factor 2 better than what could be achieved by a standard pixel detector with the same pitch → there is room for significant improvement, we need to increase signals
- **Intense R&D activities ongoing**: new RSD productions coming soon, working on a dedicated RSD read-out board, new reconstruction algorithms being developed

Thank You!

Acknowledgements

- The measurements leading to these results have been performed at the Test Beam Facility at DESY Hamburg (Germany), a member of the Helmholtz Association (HGF)
- We kindly acknowledge the following funding agencies and collaborations:
  - INFN–CSN5, RSD Project
  - FBK-INFN collaboration framework
  - MUR PRIN project 4DInSiDe
  - Dipartimenti di Eccellenza, Torino University (ex L.232/2016, art. 1, cc. 314, 337)

The research leading to these results has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement no. 101057511

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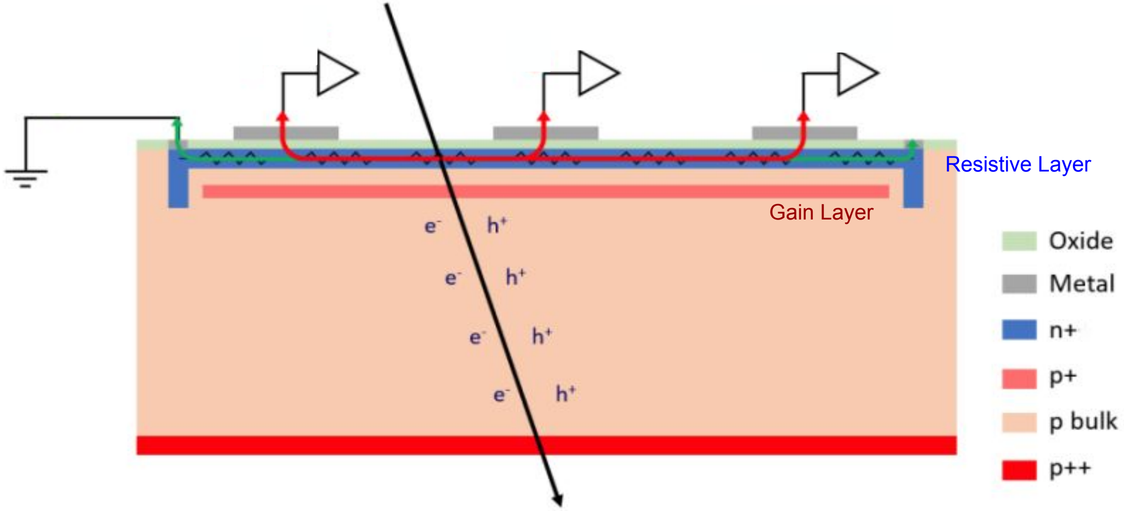
BACKUP

Principle of Operation

1) A ionizing particle produces e-h pairs in the sensor bulk, electrons are multiplied in the gain region
2) Charge is induced on the resistive layer and propagates
3) The AC pads close to the hit position see a fast signal, thanks to the capacitive coupling to the resistive layer
4) Charge flow to ground, AC pads discharge



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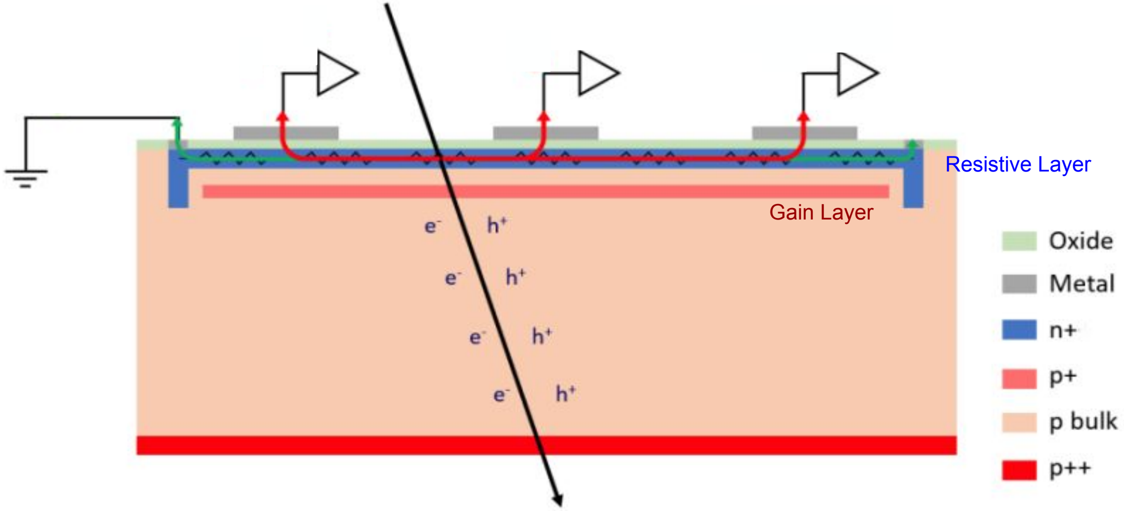

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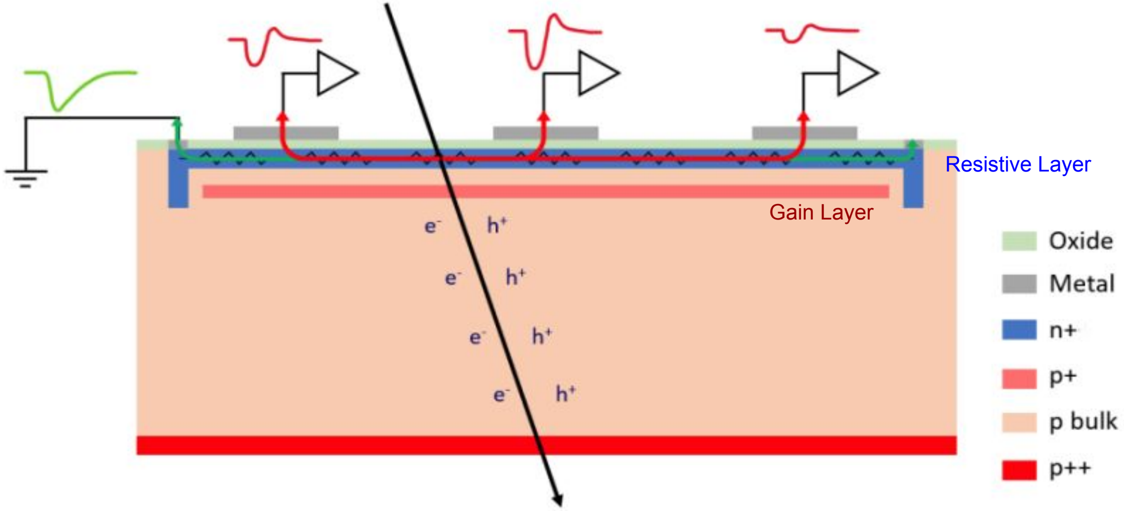

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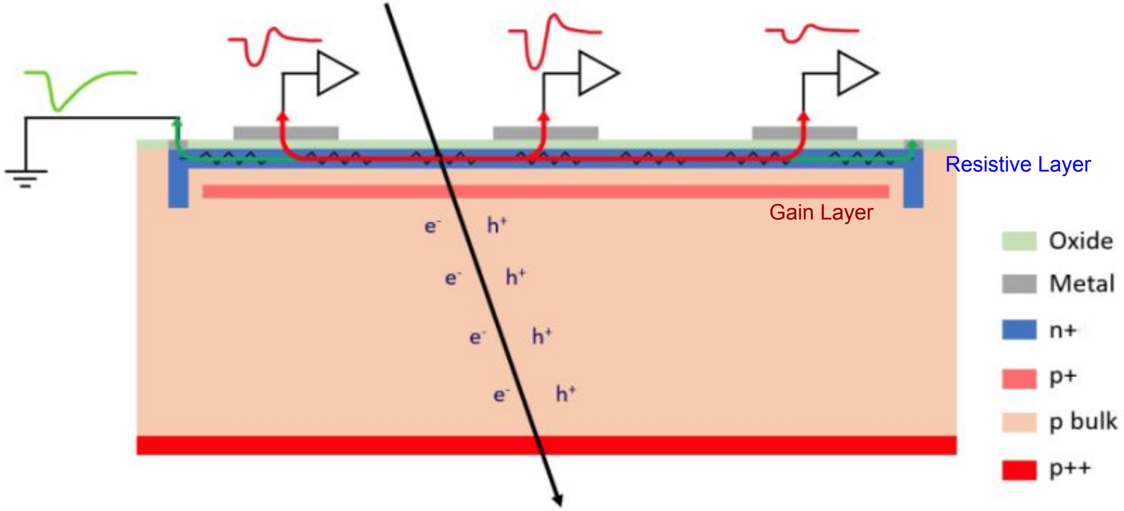
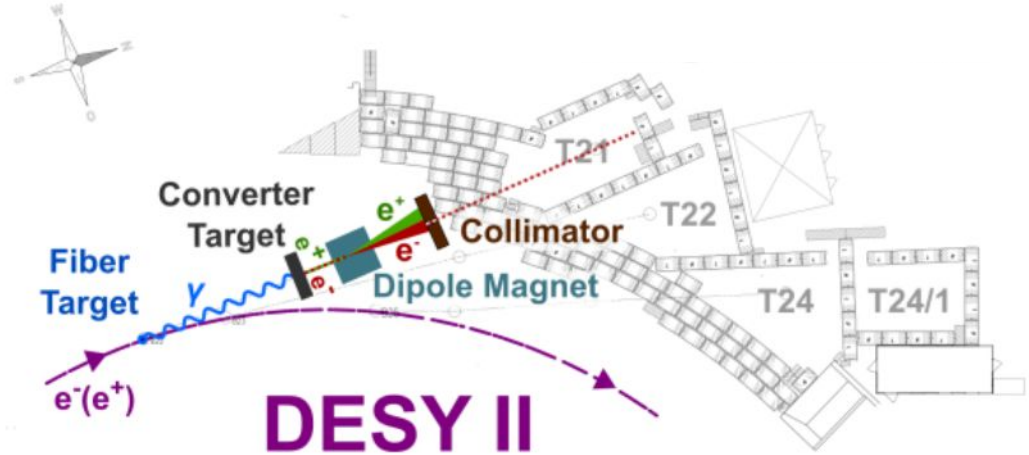


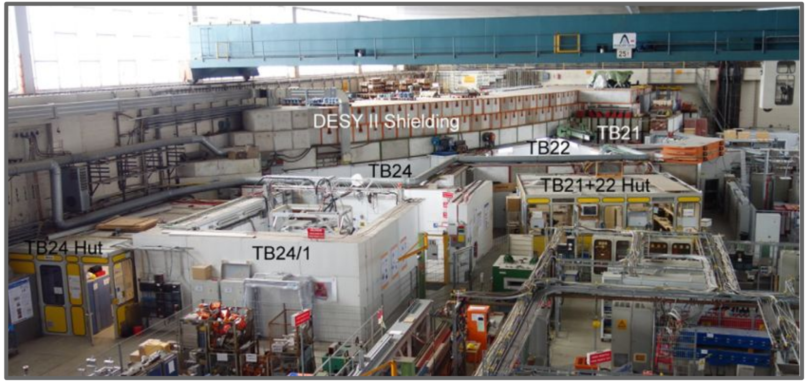
DESY Test Beam Facility

The DESY II test beam facility”
(https://doi.org/10.1016/j.nima.2018.11.133)
NIMA, Vol. 922, 2019

- **1 - 6 GeV electron / positron** beam
- ***O*(10k) particles s^{-1}cm^{-2}** rate
- The facility is equipped with EUDET-type **pixel beam telescopes with estimated ~ 15 um spatial resolution** (can go down to 2um in ideal conditions)

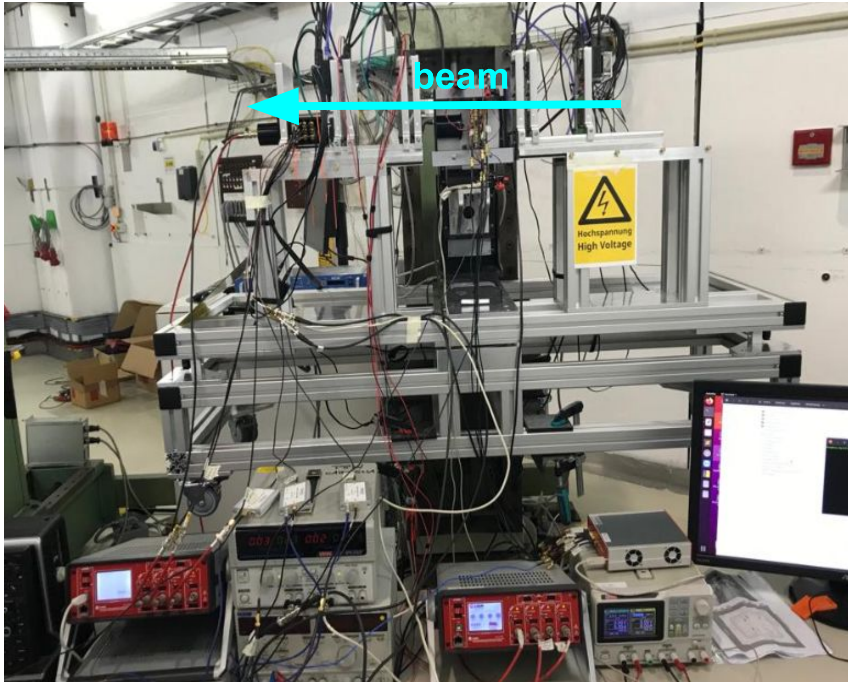


Picture of the test beam facility



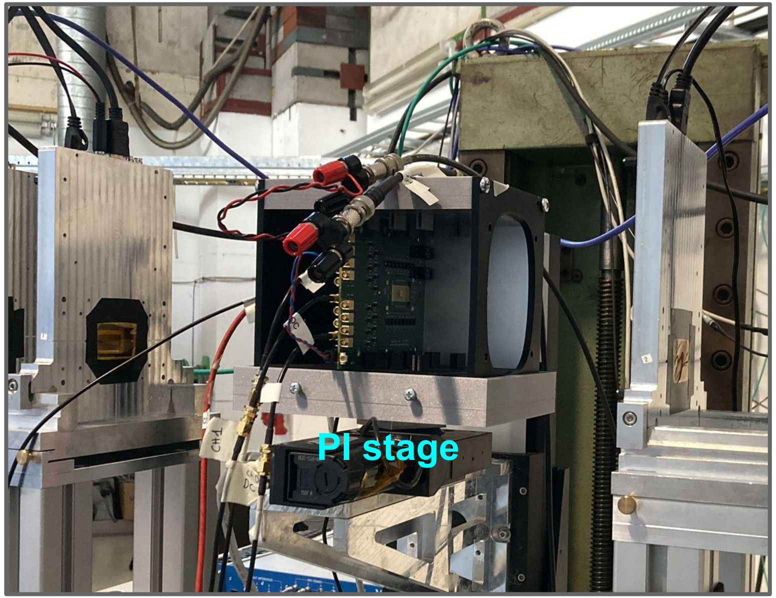
Setup - 1

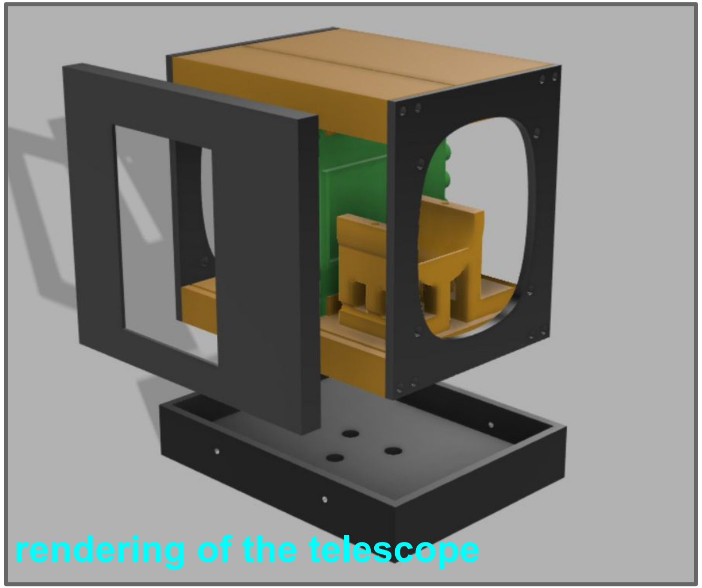
- Energy set to ~4 GeV for RSD tests
- Data acquired for ~5 days
  (@ room T, only pre-rad sensors)
- Collected *O*(100k) trigger per sensor
- A laser system provides the reference beam position
- The setup sits on a dedicated metal rack aligned with the beam



Setup - 2

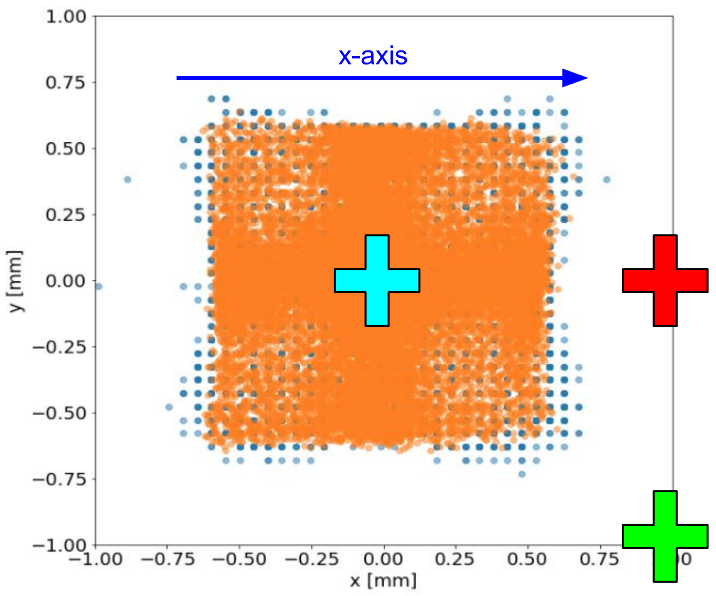
- Read-out board and digitizer are the same used during lab tests
- Trigger: a RSD2 with same active area of the DUTs, with all AC pads floating and DC-ring read out
- A 3d-printed telescope screwed on a PI stage houses DUT & trigger and ensures they are aligned

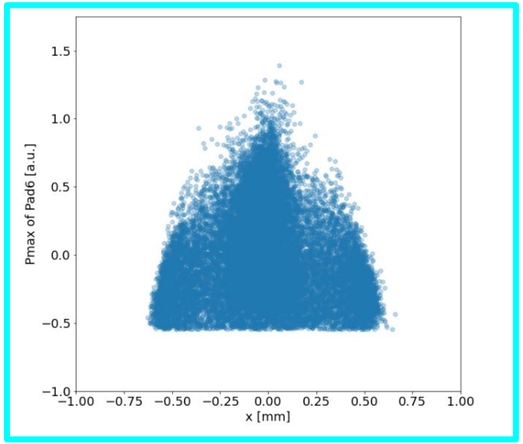




Training the Neural Network

- To understand this pattern, a glance at the input features used to train the model can be instructive
- Let’s pick 3 pads and see how their relative amplitudes change along the x-axis





Central pad has the expected trend, peaking in x=0

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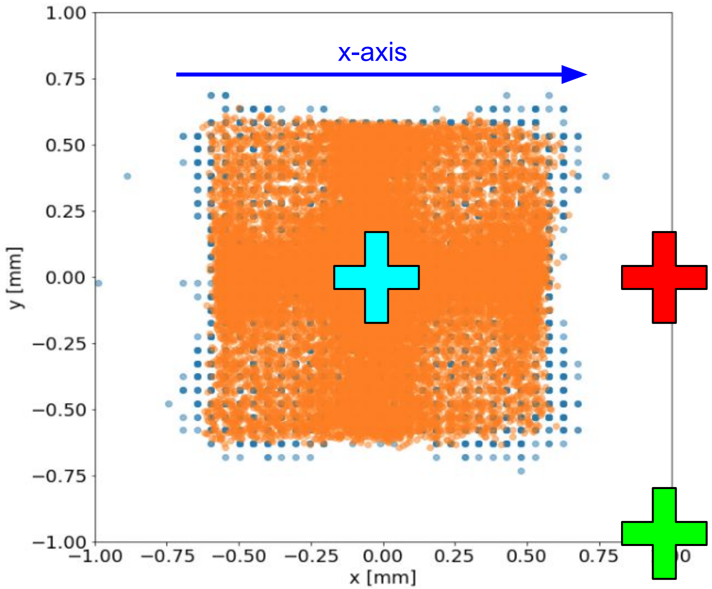

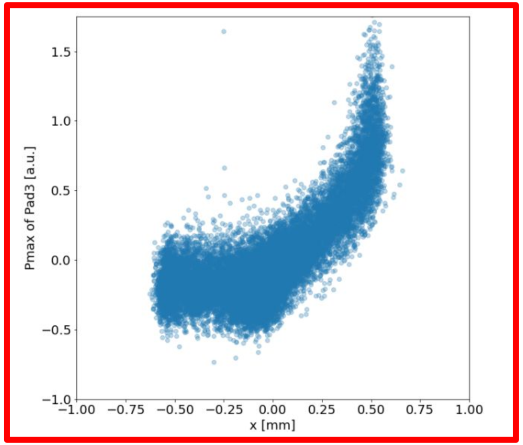

This pad has the expected trend too, with amplitude increasing while getting closer to the pad

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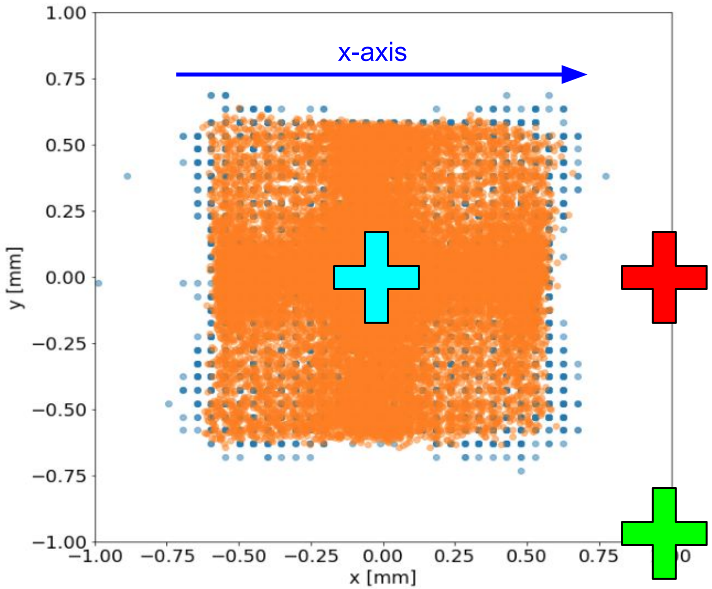
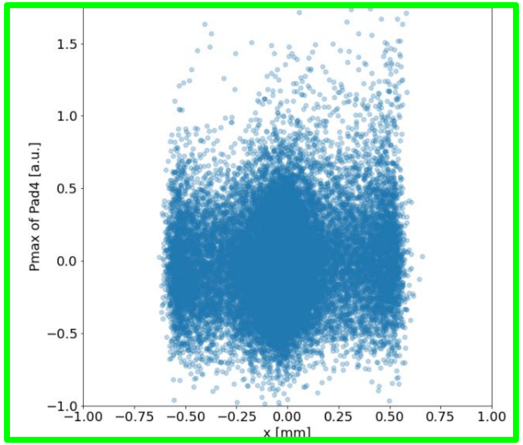


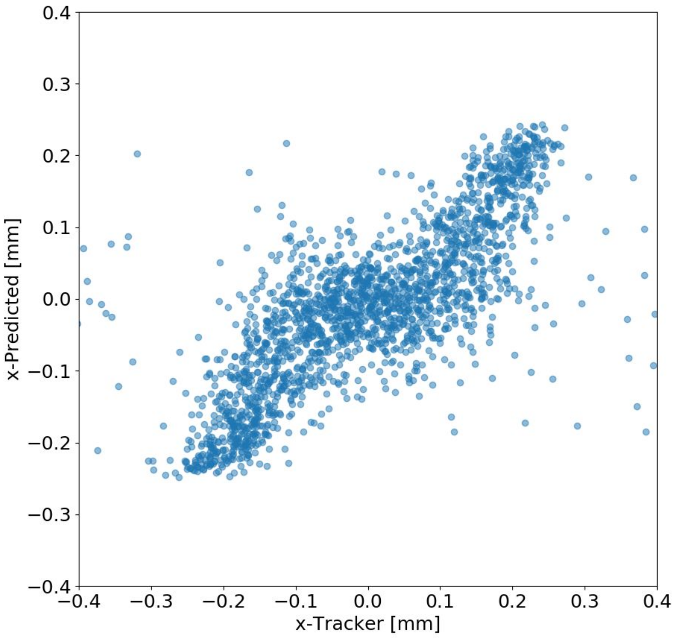


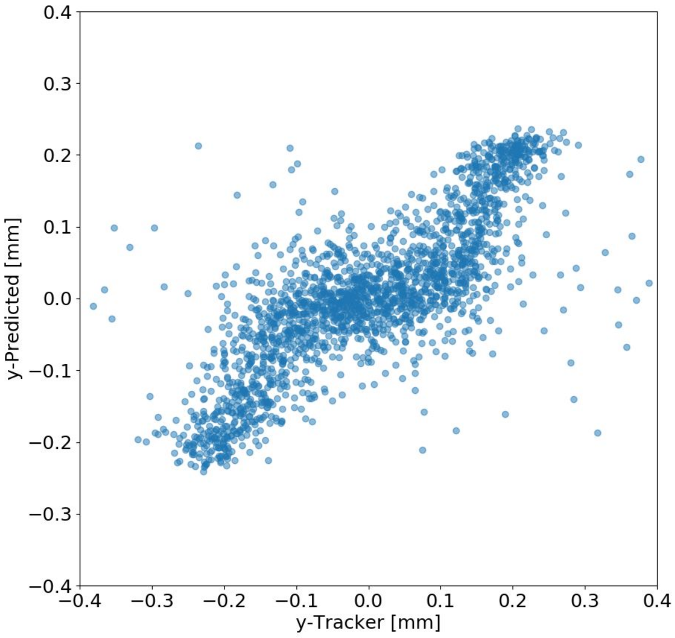
The pad on the corner sees a ~ constant signal, independent on the x-position, so it’s recording mostly noise… this is related to the sensor geometry

Results from the DESY TB

- We used the model trained with laser data to predict the DESY test beam positions
- Sensor, temperature, gain level and read-out chain are the same as laboratory tests
- The sensor achieved $\boldsymbol{\sigma_{RSD}}$ **~ 65 um**

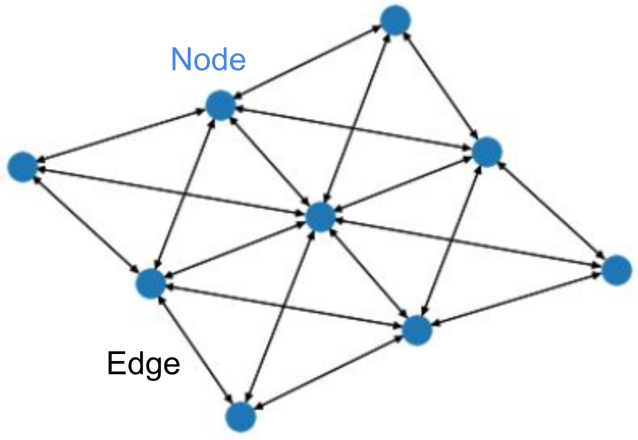
Good tracker-RSD correlation





A different model: Graph Neural Network

- Graph Neural Networks (GNNs) are powerful deep learning models that we tried to use to reconstruct the hit position with RSD
- GNNs are based on **nodes** (in our case, the pads) connected through **edges** (representing how large is the correlation between two pads)



Sketch of a graph representing the RSD

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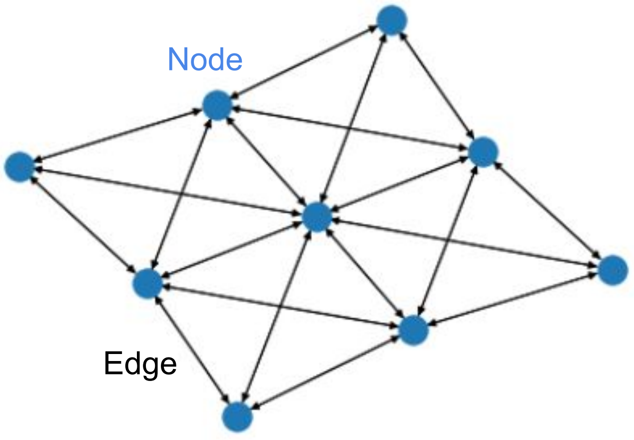

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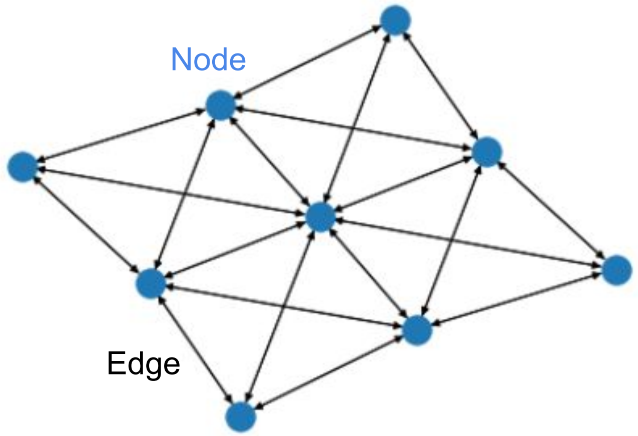
  - Each node is characterized by a set of features: the positive and negative signal amplitudes of that pad, in our case
- The idea is to use a **GNN followed by the usual dense NN**: the GNN changes the input features fed to the NN by embedding information from the neighbouring pads, possibly enhancing the model accuracy



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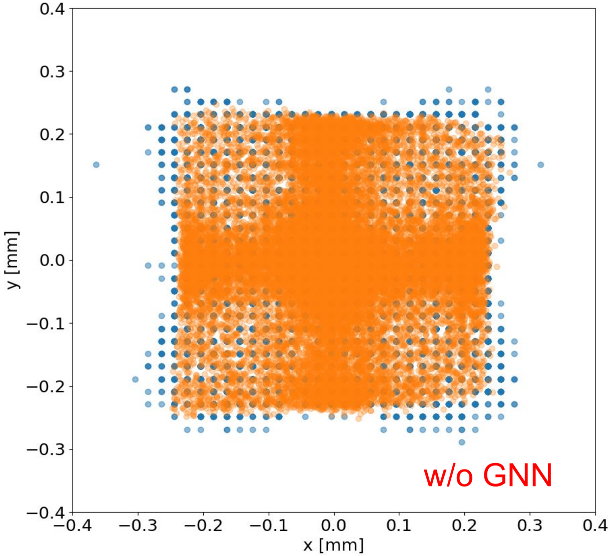
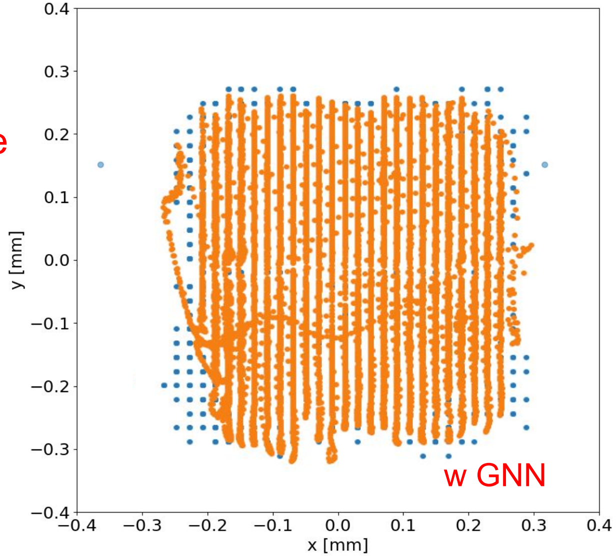
- As of today, only very preliminary results are available
- One interesting feature is that the predicted positions do not show patterns as with the NN only, rather they arrange in the same grid as the reference positions, underlining the strength of this method



Predictions using the laser training dataset, with and without the use of a GNN



laser reference
prediction

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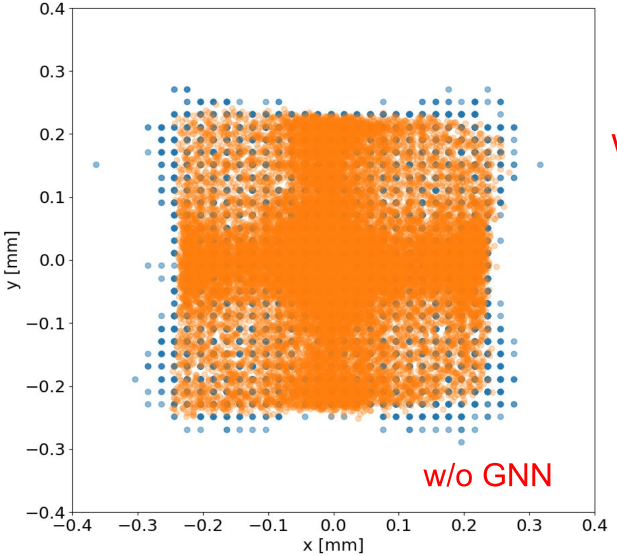
- One interesting feature is that the predicted positions do not show patterns as with the NN only, rather they arrange in the same grid as the reference positions, underlining the strength of this method
- A big flaw, however, is that presently we are not able to generalize the model and so to make predictions on different datasets



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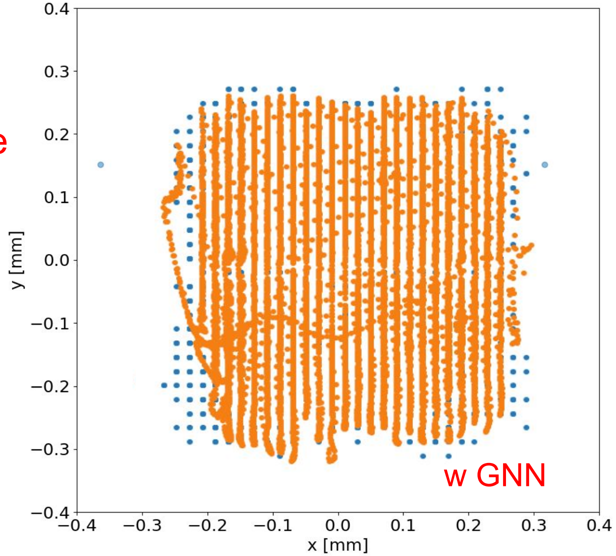

laser reference
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