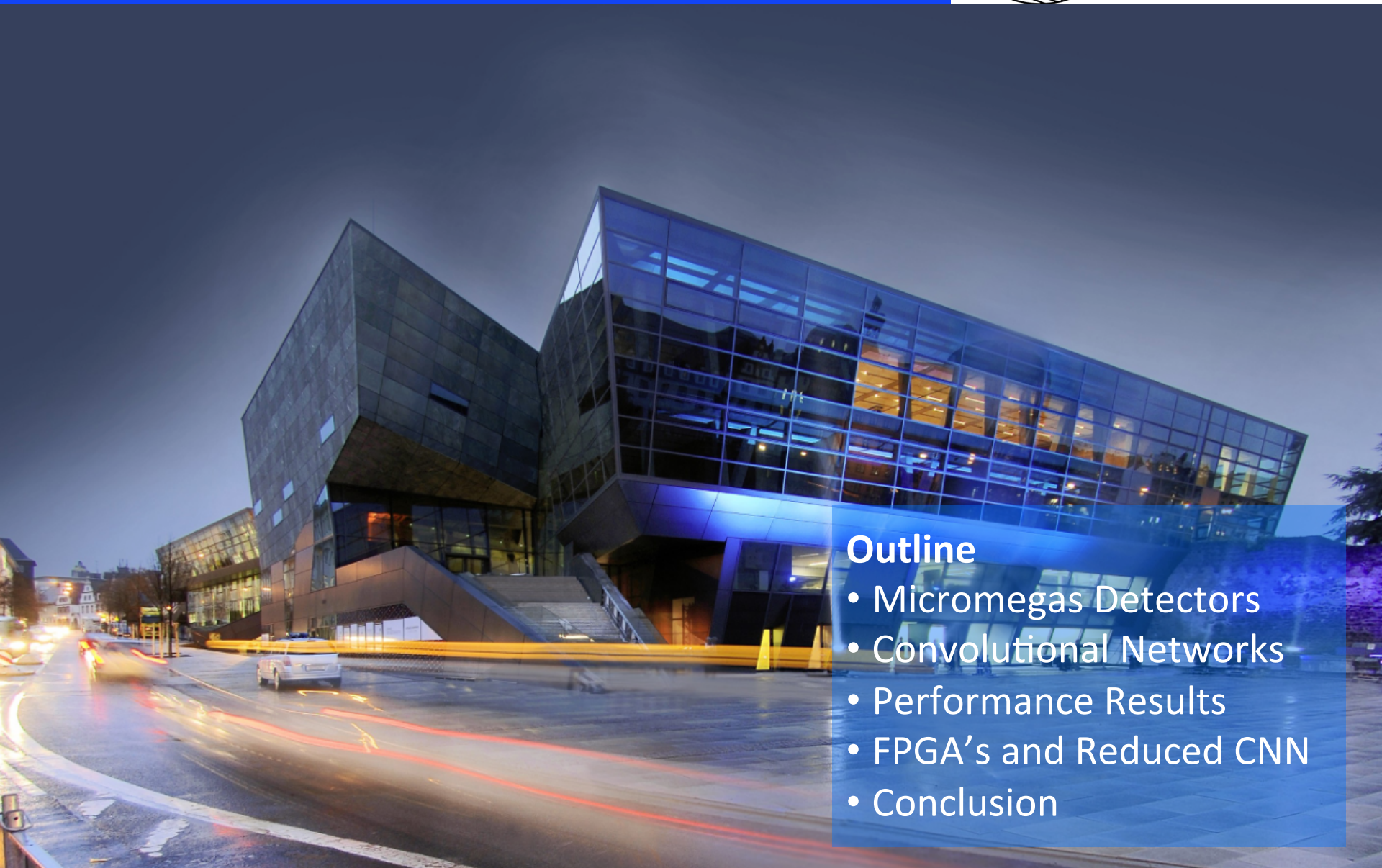
Reconstruction of Micropattern Detector Signals using Convolutional Neural Networks

L. Flekova (TU Darmstadt), M. Schott (Uni Mainz)

TECHNISCHE UNIVERSITÄT DARMSTADT



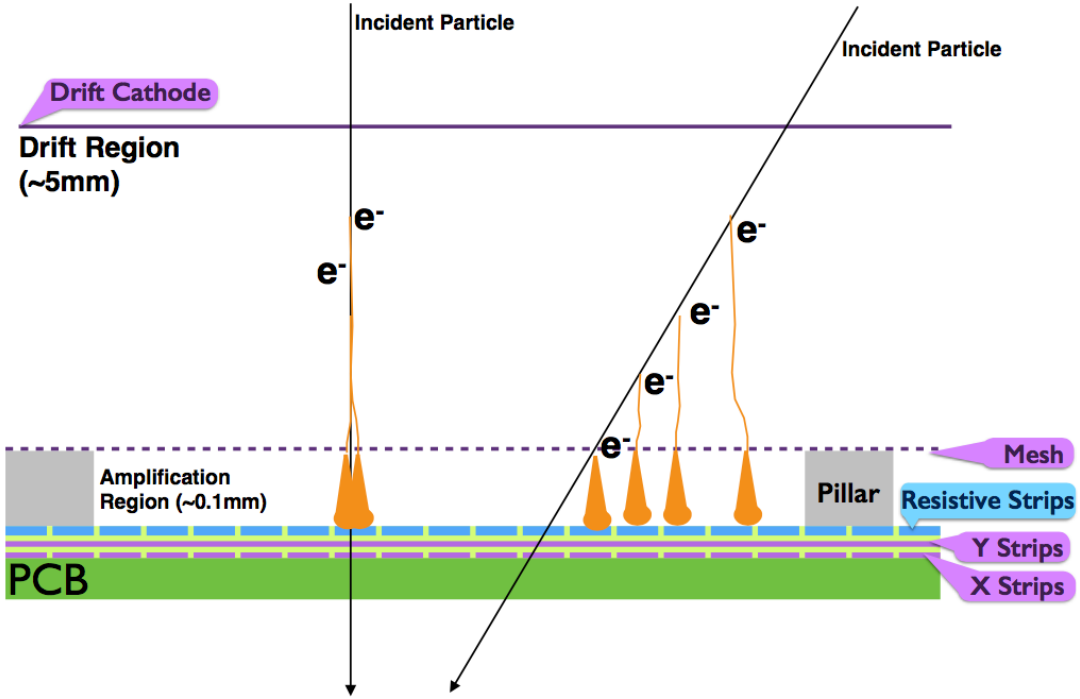
Outline

- Micromegas Detectors
- Convolutional Networks
- Performance Results
- FPGA's and Reduced CNN
- Conclusion

Micromegas Detectors

TECHNISCHE UNIVERSITÄT DARMSTADT

- Incident particles ionize gas-atoms (Ar/CO_2)
  - Resulting electrons drift towards amplification mesh
- Electric field in amplification is high enough to cause avalanches



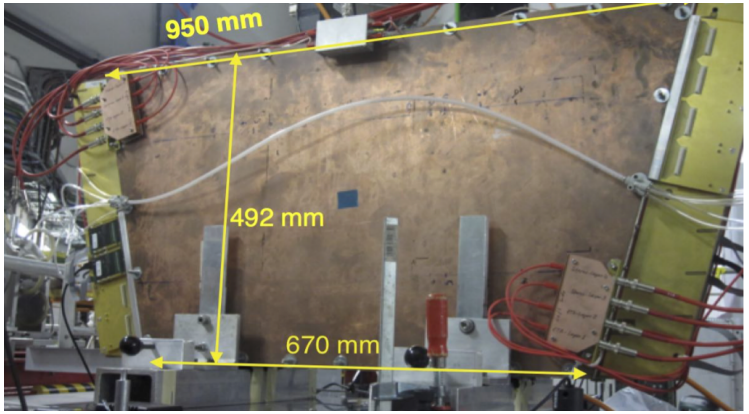
- Amplification of 10^3-10^4 of primary electrons, which induce charge at readout-strips
- Sparking can be prevented by resistive strips on top of readout layers

Possible Applications

TECHNISCHE UNIVERSITÄT DARMSTADT

- Micromegas detectors are low-cost alternatives for tube-chambers, with
  - high background rate stability
  - good spatial (40μm)
  - and timing resolution (5ns)

- Applications
  - Small areas in CAST and COMPASS
  - First large scale application: ATLAS Upgrade of the Muon Systems
  - Future: Any high-rate, large-area environment

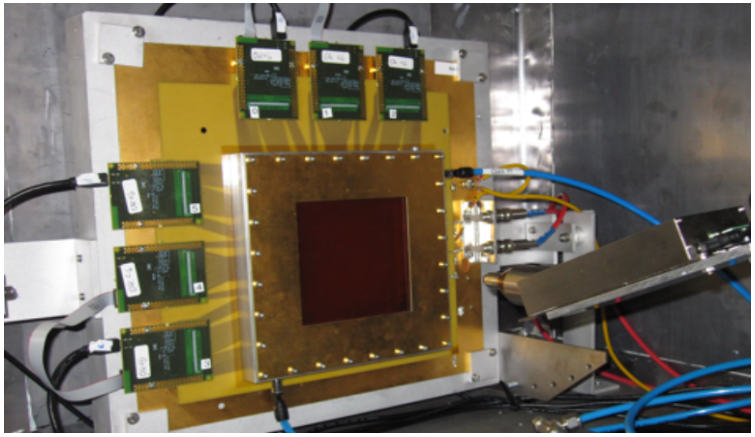


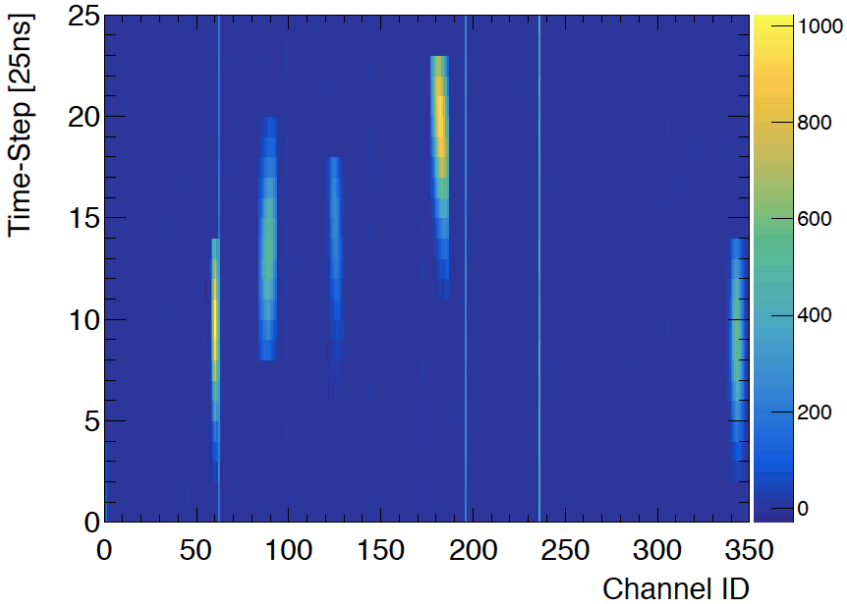
Signals and Readout

TECHNISCHE UNIVERSITÄT DARMSTADT

- Most current Micromegas detectors in HEP are readout through APV25 hybrid cards
  - 128 channels readout in 25 time-steps stored at 40 Mhz rate
  - Analog CR-RC shaped signals gives information on measured charge on channel

- Goal: Efficiently **identify** particles and determine **spatial-position** and **signal-time**
  - Use Convolutional Neural Network (on FPGA's)

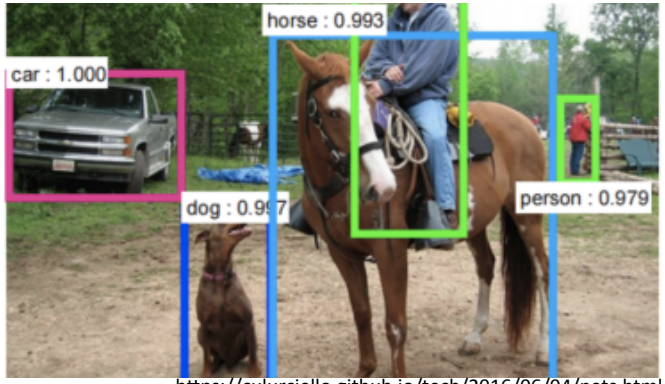




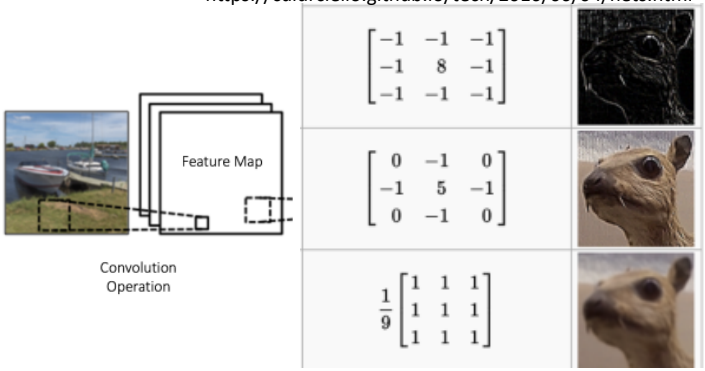
Conv. Neural Networks

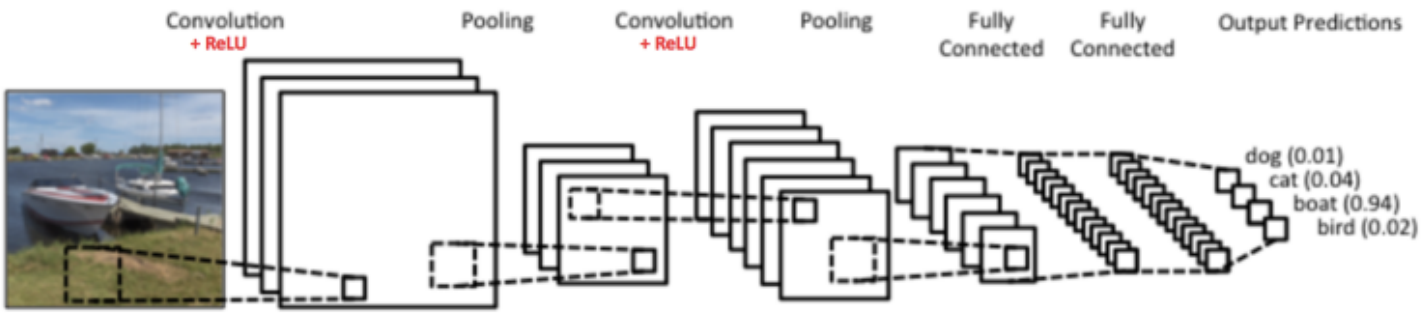
TECHNISCHE UNIVERSITÄT DARMSTADT

- Fully connected networks do not scale well (one node for each pixel) and do not take into account spatial information (pixel far apart treated the same as neighboring ones)
- In CNN filters learn specific features at spatial positions of input
- Local connectivity
- Shift-invariant

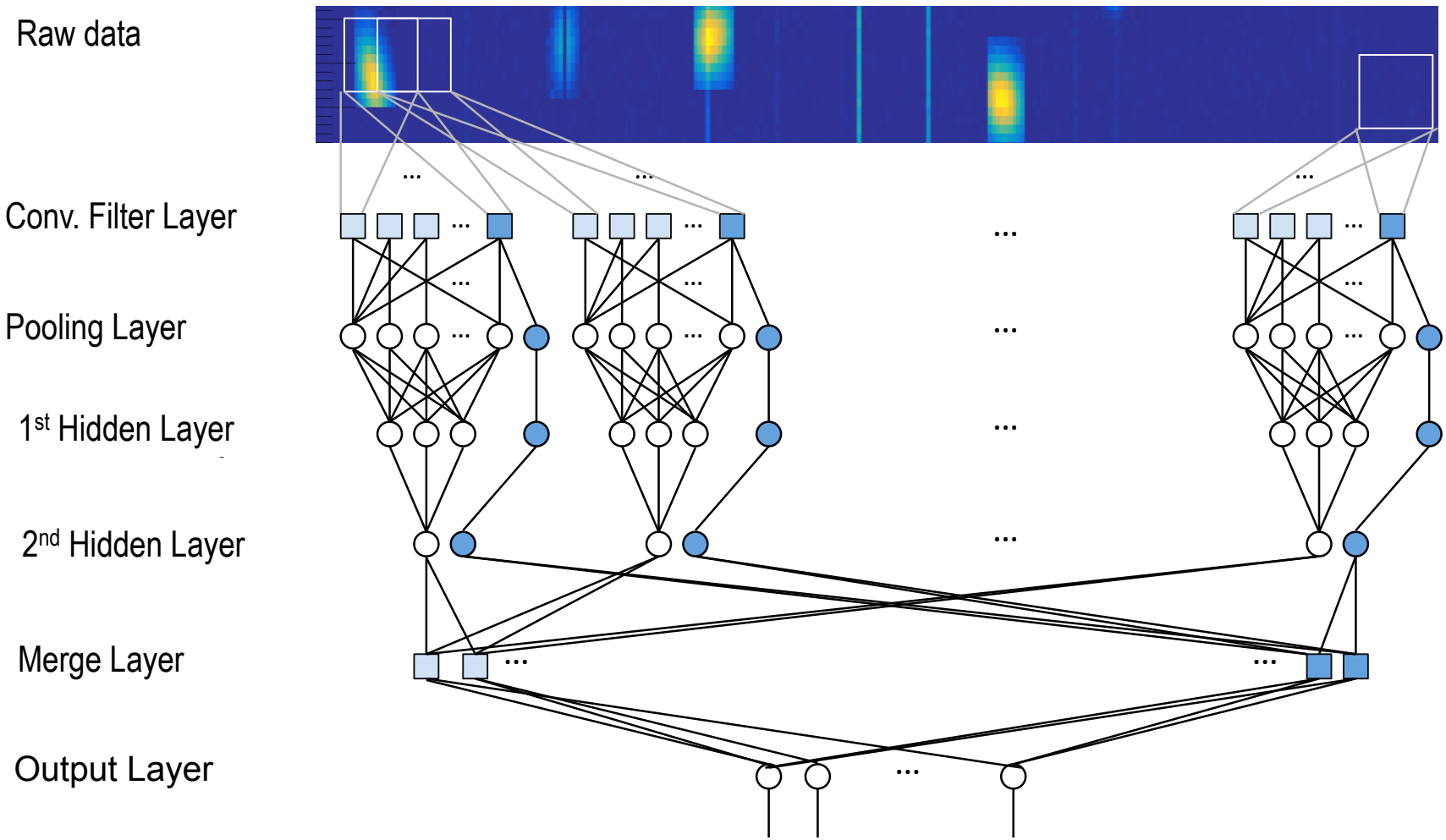


https://culurciello.github.io/tech/2016/06/04/nets.html





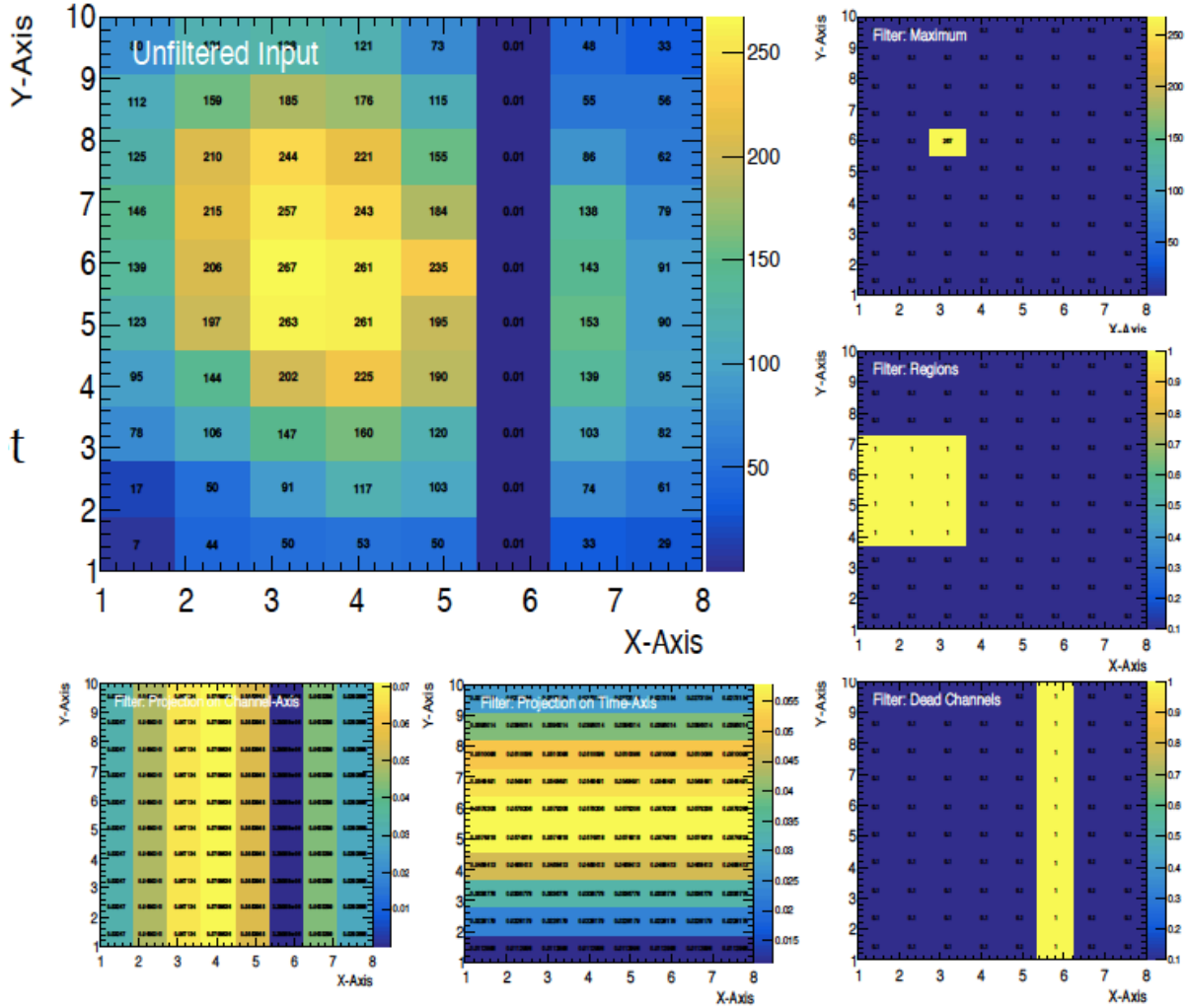
Network Architecture



Filter Layer

TECHNISCHE UNIVERSITÄT DARMSTADT

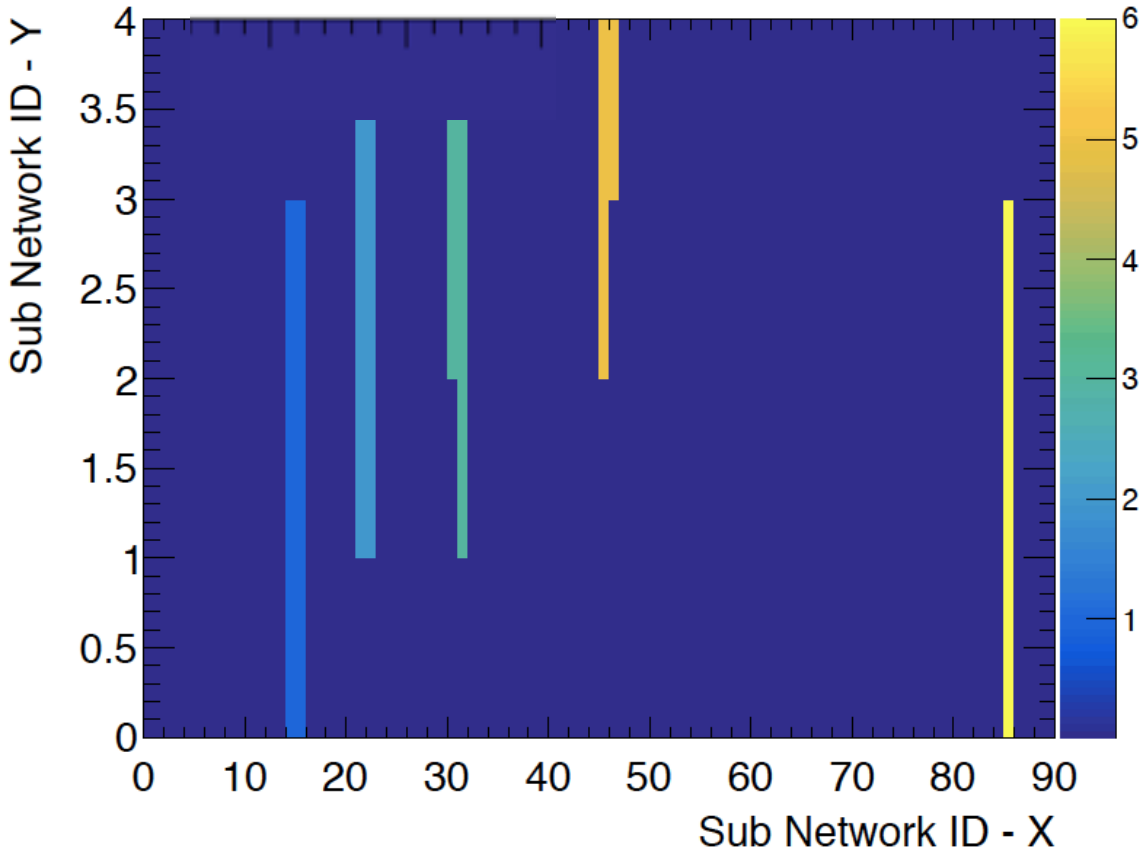
- Several filter types extract relevant shape characteristics
- Information reduced per subset from 80 input variables to 20
- Maximum filter via weighted mean used for position extraction



Merge Layer

TECHNISCHE UNIVERSITÄT DARMSTADT

- Information of all networks gets combined and clusters restructured
- 360x25 input reduced to 90x4
- Output: Common regions of identified clusters



Dataset and Training

TECHNISCHE UNIVERSITÄT DARMSTADT

- Use MC simulated events of event signatures, in order to quantify resolution performance
  - Include typical signal characteristics
  - Background noise
  - Dead channels
  - Overlapping signals

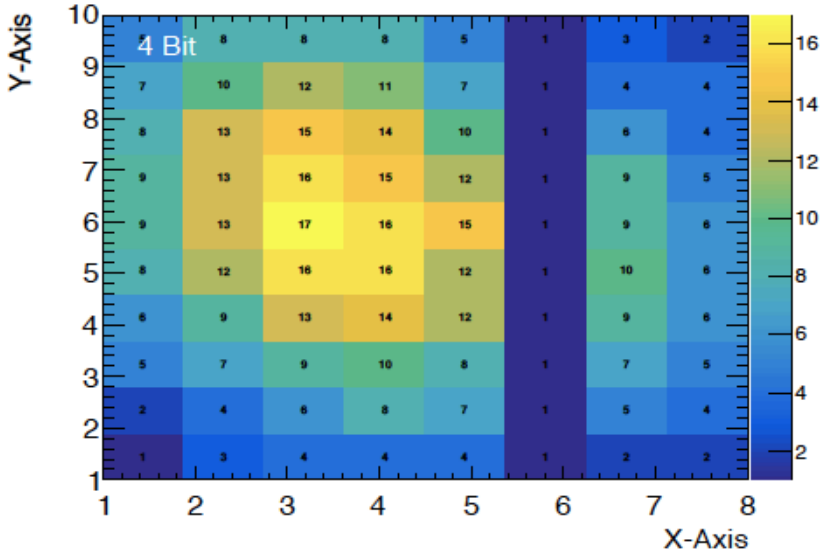
- Results are cross-checked with real detector data

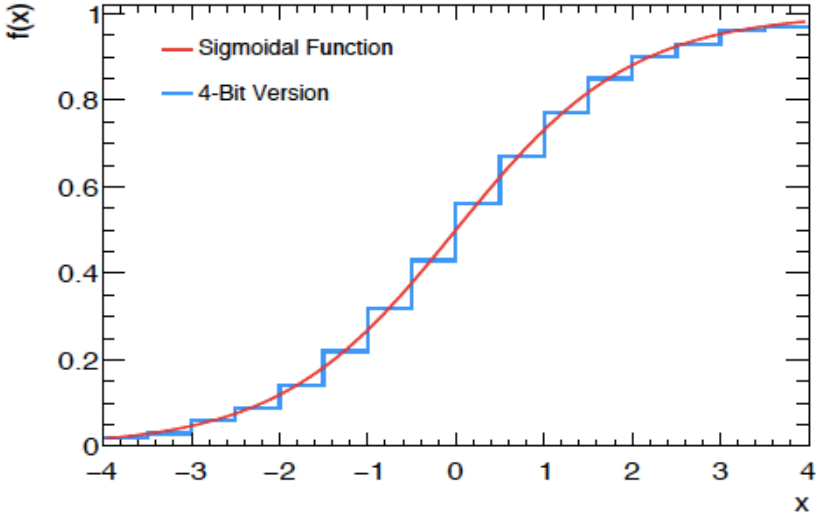
- First filter layer optimized to be parallelized as much as possible
- Advanced backpropagation algorithm for training

Discretization for FPGA

TECHNISCHE UNIVERSITÄT DARMSTADT

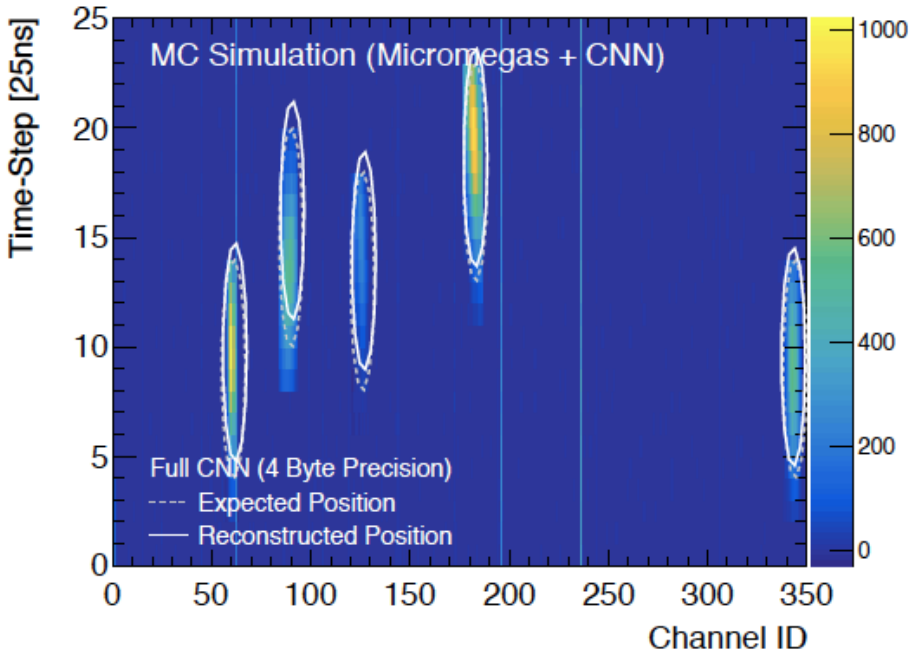
- Training is performed using floating point precision
- Input to FPGA has to be reduced to allow for the limited band-width (+operations on FPGA)
- Input-patterns reduced to 4-bit
- Weights reduced to 6-bit
- Sigmoidal reduced to 4-bit

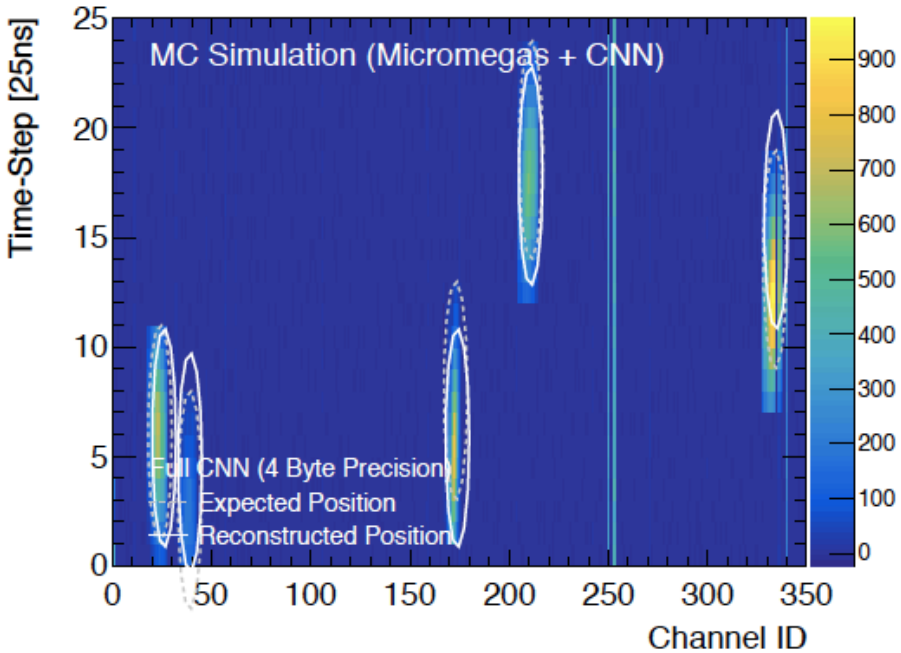




First Results

TECHNISCHE UNIVERSITÄT DARMSTADT



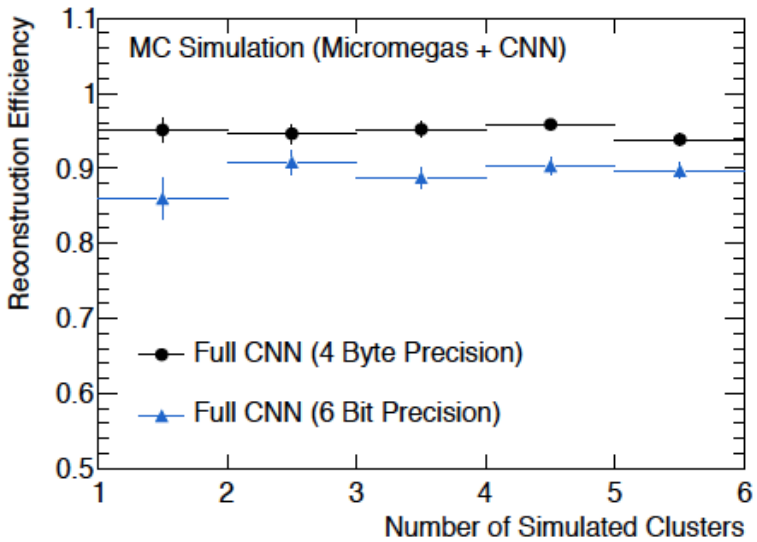


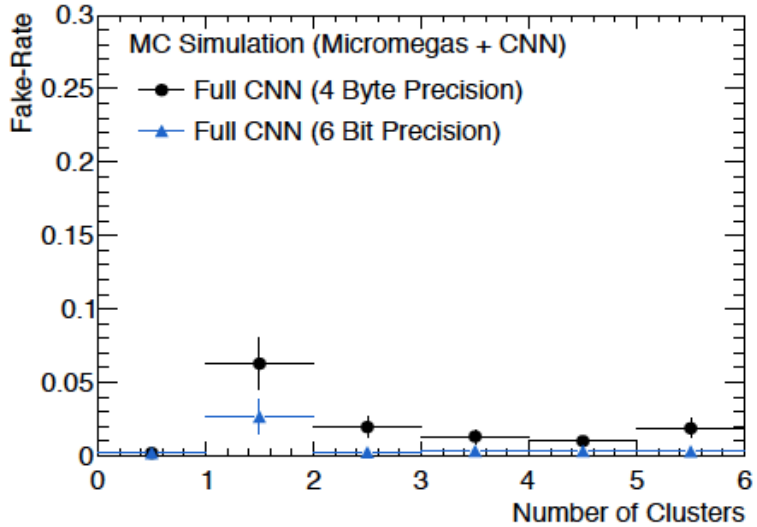
- Total **training set of 20k events** with different background and detector features
  - Each event has between 0-5 individual particle signatures
- Uncorrelated test statistics of 1k events + real detector data

Efficiency & Fake Rates

TECHNISCHE UNIVERSITÄT DARMSTADT

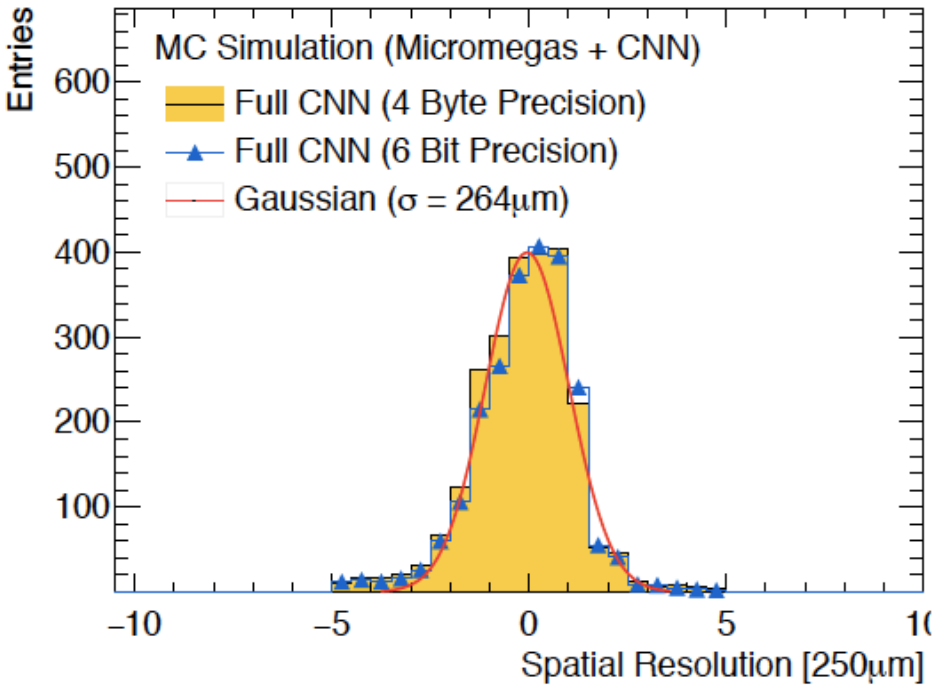
- A particle is identified correctly if the reconstructed position is within 1mm of the expected position
  - otherwise fake reconstruction
- **Reconstruction efficiency >90%** for full network information
  - >85% for reduced values
  - No dependency on number of particles per event
- **Fake rate <5%** and is an artifact of spatial resolution

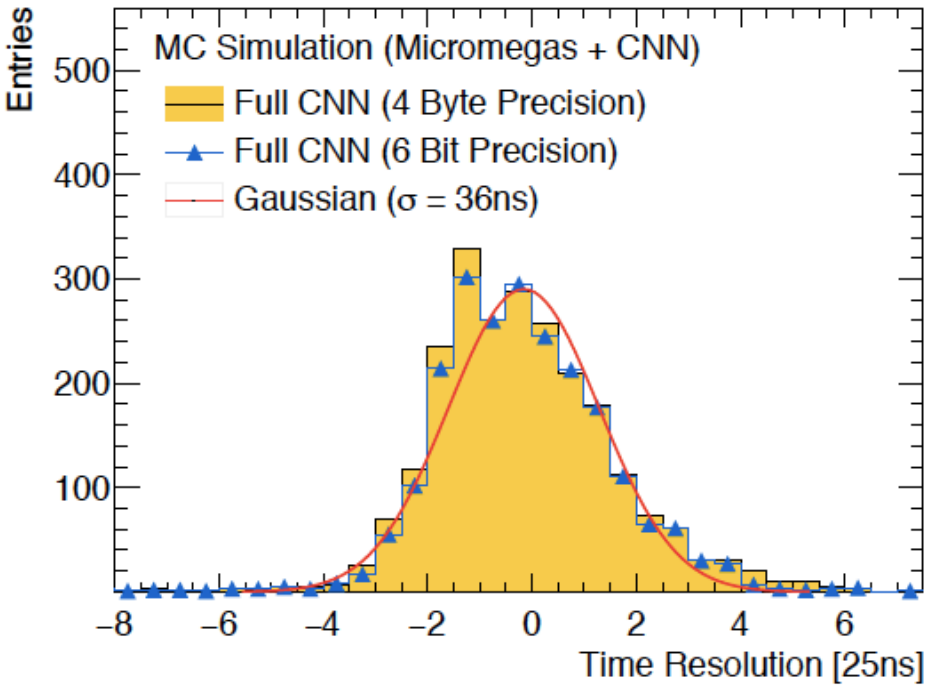




Resolutions

TECHNISCHE UNIVERSITÄT DARMSTADT



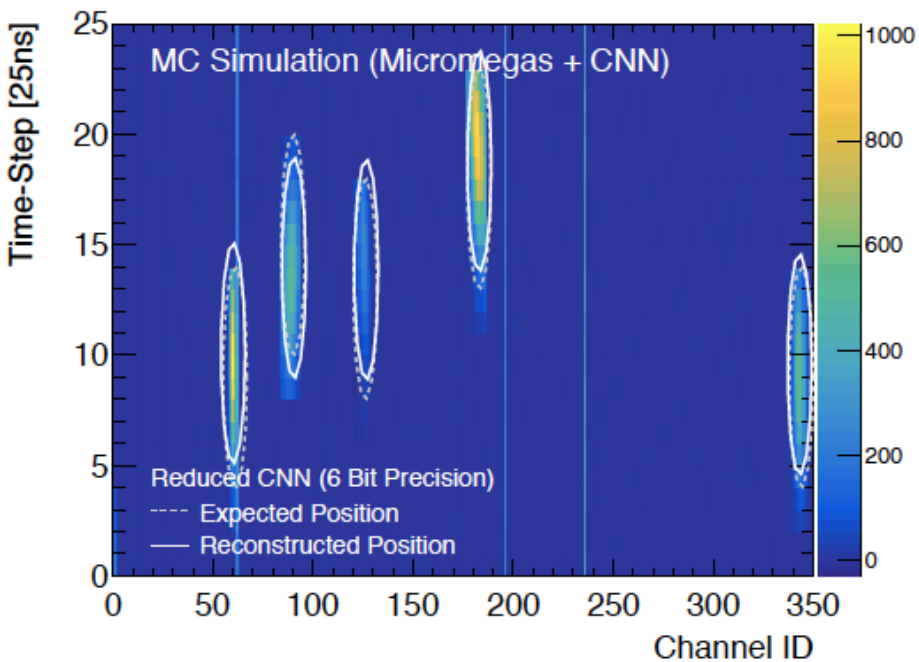


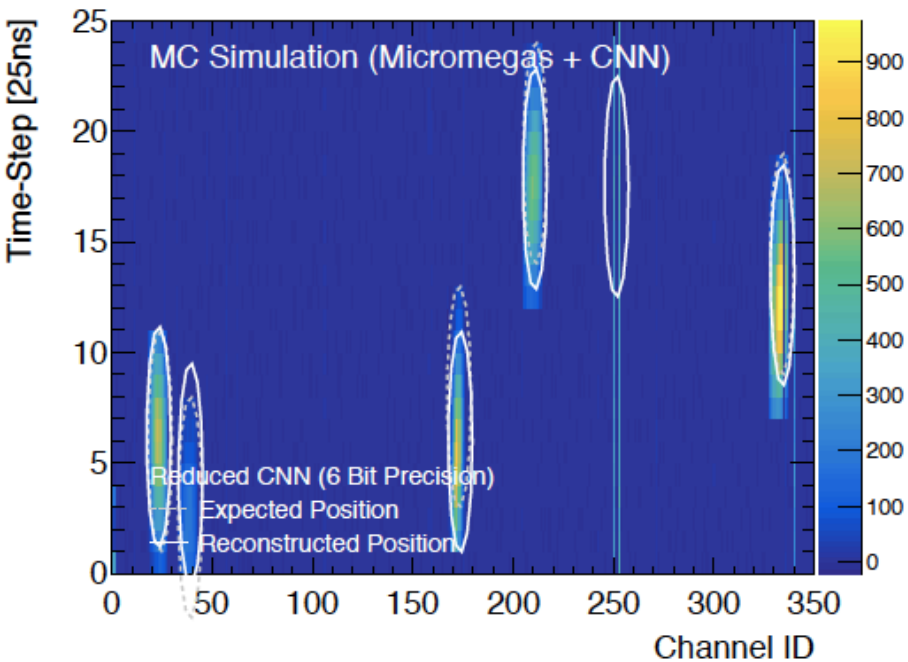
- Spatial resolution ≈250μm (=width of readout strip) for 4 Byte and 6 Bit precision similar
  - Full reconstruction allows for 50μm
- Similar timing resolution of 36ns for both approaches

Further Input Reduction

TECHNISCHE UNIVERSITÄT DARMSTADT

- Input of 360x25 values too large for typical FPGA's (600-1000 bits per cycle)
  - Corresponds to a detector of 25-50cm in length
- Reduce input information to 90x4 values (5 cycles to read-in) before filtering

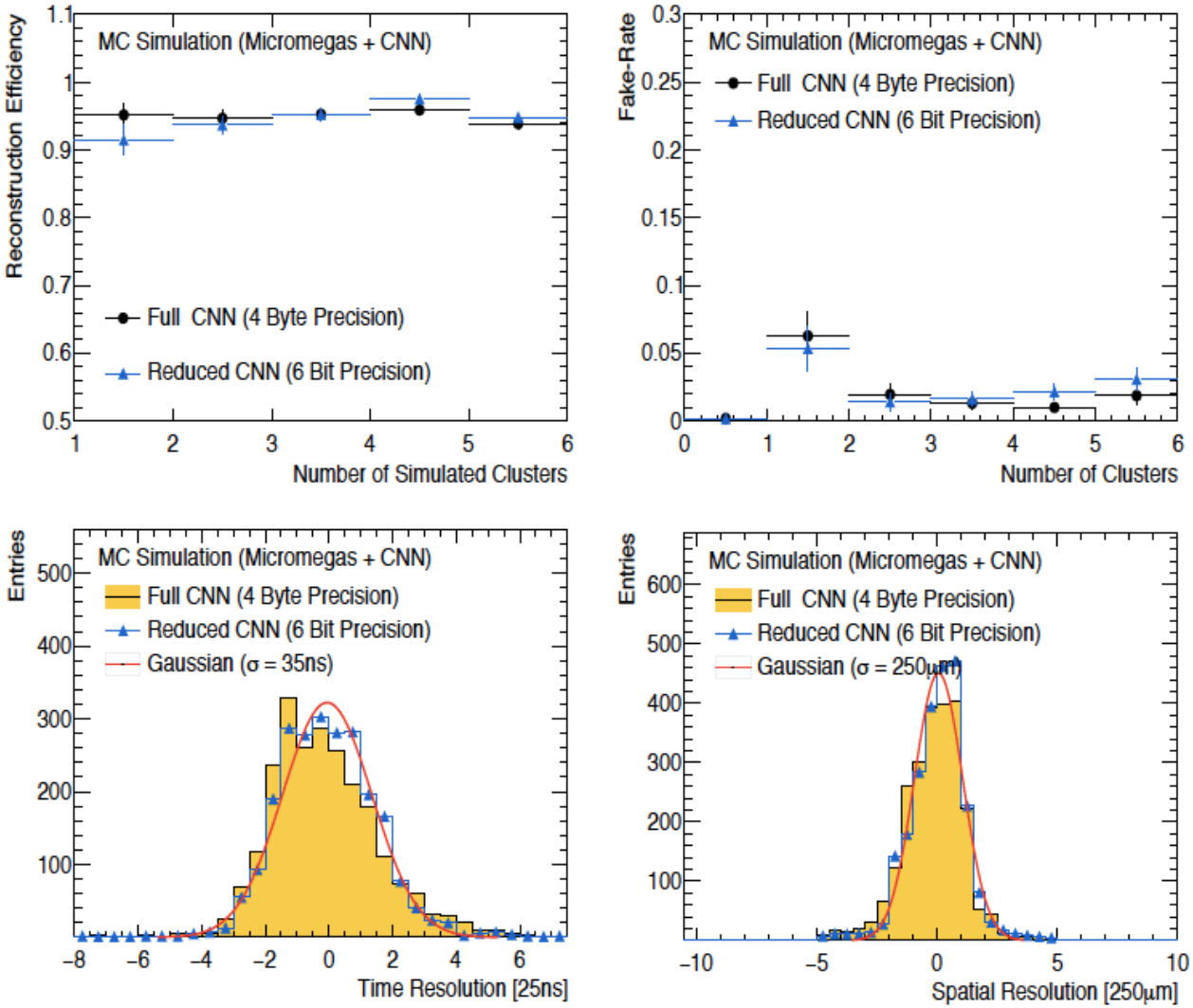




Performance Estimate

TECHNISCHE UNIVERSITÄT DARMSTADT

- Reduced setup very similar performance to full CNN
- No dependence on number of signal clusters
- No increase of fake-reconstructions

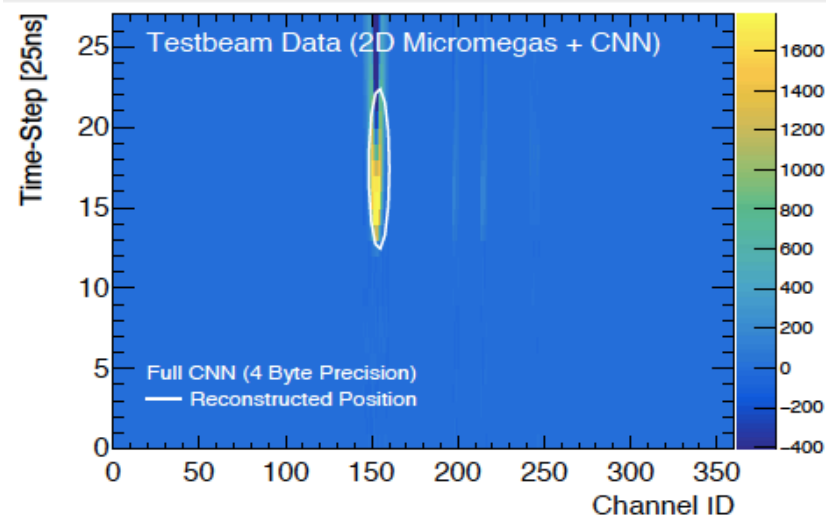


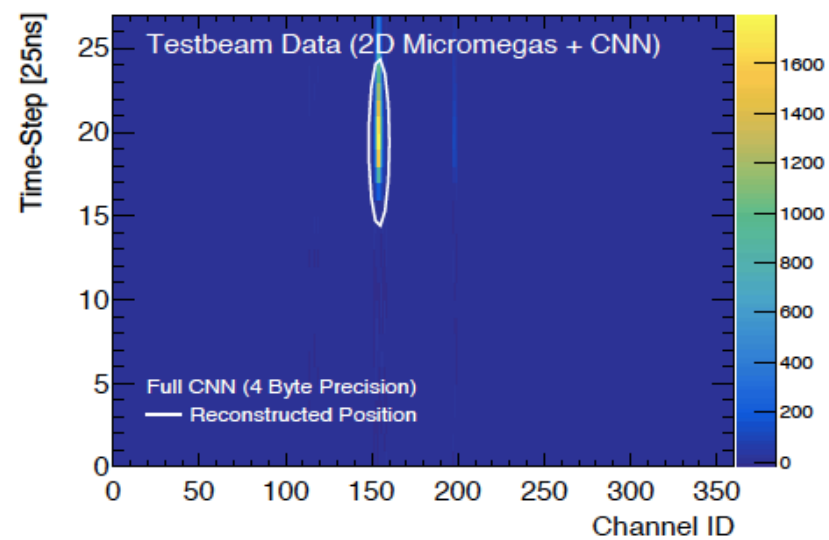
Testbeam Data

TECHNISCHE UNIVERSITÄT DARMSTADT

- Reduced CNN has been tested with real data taken at
  - Testbeam at MAMI electron accelerator at JGU Mainz
  - GIF++ facility at CERN (high background rates)
  - See in both cases reconstruction **efficiencies >90%**

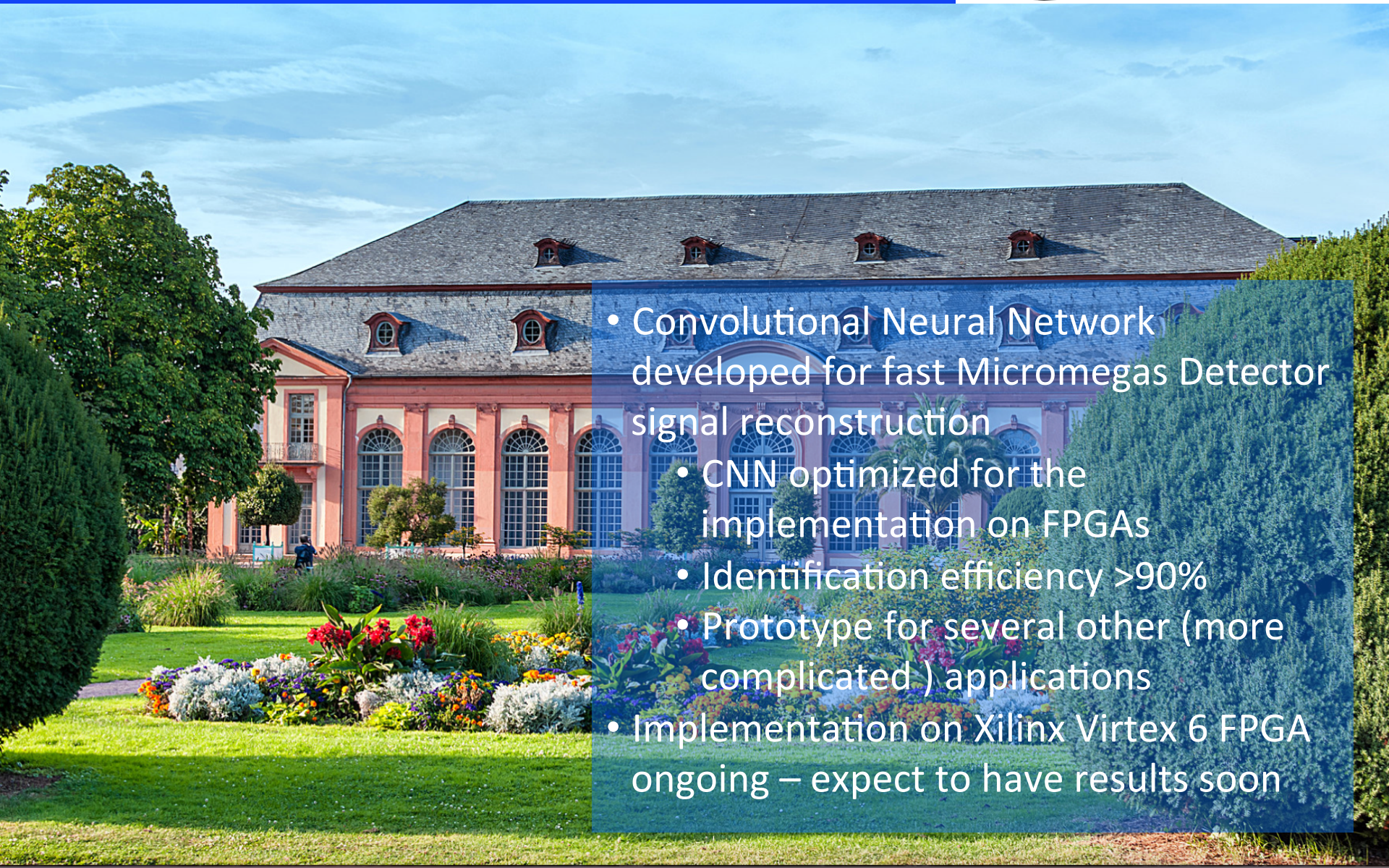
- Reduced CNN is currently implemented on standard FPGA (Xilinx Virtex 6) is expected to generate results in 30-50 cycles (approx 100 ns)





Summary & Next Steps

TECHNISCHE UNIVERSITÄT DARMSTADT



- Convolutional Neural Network developed for fast Micromegas Detector signal reconstruction
  - CNN optimized for the implementation on FPGAs
  - Identification efficiency >90%
  - Prototype for several other (more complicated) applications
- Implementation on Xilinx Virtex 6 FPGA ongoing – expect to have results soon