Area C Overview

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IDT-UM Meeting

September 21, 2020

CLUSTER OF EXCELLENCE
QUANTUM UNIVERSE

Universität Hamburg
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Partnership of
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Introduction

Reminder: Structure of Area C
Deep Learning, Erkenntnisgewinn durch fundierte datengetriebene Methoden

C1) Sensornahe Verarbeitung von Daten	**C2) Objektrekonstruktion**
• Signalfilter, Rauschunterdrückung • Verarbeitung von zeitabhängigen Signalen	• Spur- und Clusterrekonstruktion, Jetbildung, Ereignisrekonstruktion • Fragestellungen für Anordnung, Reihenfolge, Zuordnungen von Daten • Optimierungen zur Extraktion kleiner Signale bei großem Untergrund
C3) Netzwerkbeschleunigte Simulationen	**C4) Qualität von Netzwerkvorhersagen**
• Generative adversarial networks, Anpassung von Simulationen an Datenverteilungen • Evaluationsverfahren für die Qualität der Netzwerksimulationen	• Reduzierung experimenteller systematischer Unsicherheiten • Spezielle Lernstrategien • Vorhersagenrelevante Information • Unsicherheiten von Vorhersagen

Updates

C1) Sensornahe Verarbeitung von Daten

- Signalfilter, Rauschunterdrückung
- Verarbeitung von zeitabhängigen Signalen

C2) Objektrekonstruktion

- Spur- und Clusterrekonstruktion, Jetbildung, Ereignisrekonstruktion
- Fragestellungen für Anordnung, Reihenfolge, Zuordnungen von Daten
- Optimierungen zur Extraktion kleiner Signale bei großem Untergrund

C3) Netzwerkbeschleunigte Simulationen

- Generative adversarial networks, Anpassung von Simulationen an Datenverteilungen
- Evaluationsverfahren für die Qualität der Netzwerksimulationen

C4) Qualität von Netzwerkvorhersagen

- Reduzierung experimenteller systematischer Unsicherheiten
- Spezielle Lernstrategien
- Vorhersagenrelevante Information
- Unsicherheiten von Vorhersagen

Fast processing of data close to sensors (C1)

Reminder: Aim of the project in Mainz

- **Processing of detector data at extremely high rates**
  - Not possible to store data due to its size
  - Usage of GPUs not possible due to their too high latency
  - Data has to be processed and filtered locally in real-time, maybe directly at the corresponding sensors
- **Solution: deep neural networks** as replacement for iterative algorithms, that can be **efficiently evaluated on FPGAs**
- **Test environment: ATLAS L1 Trigger** (40 MHz event rate)

Current status

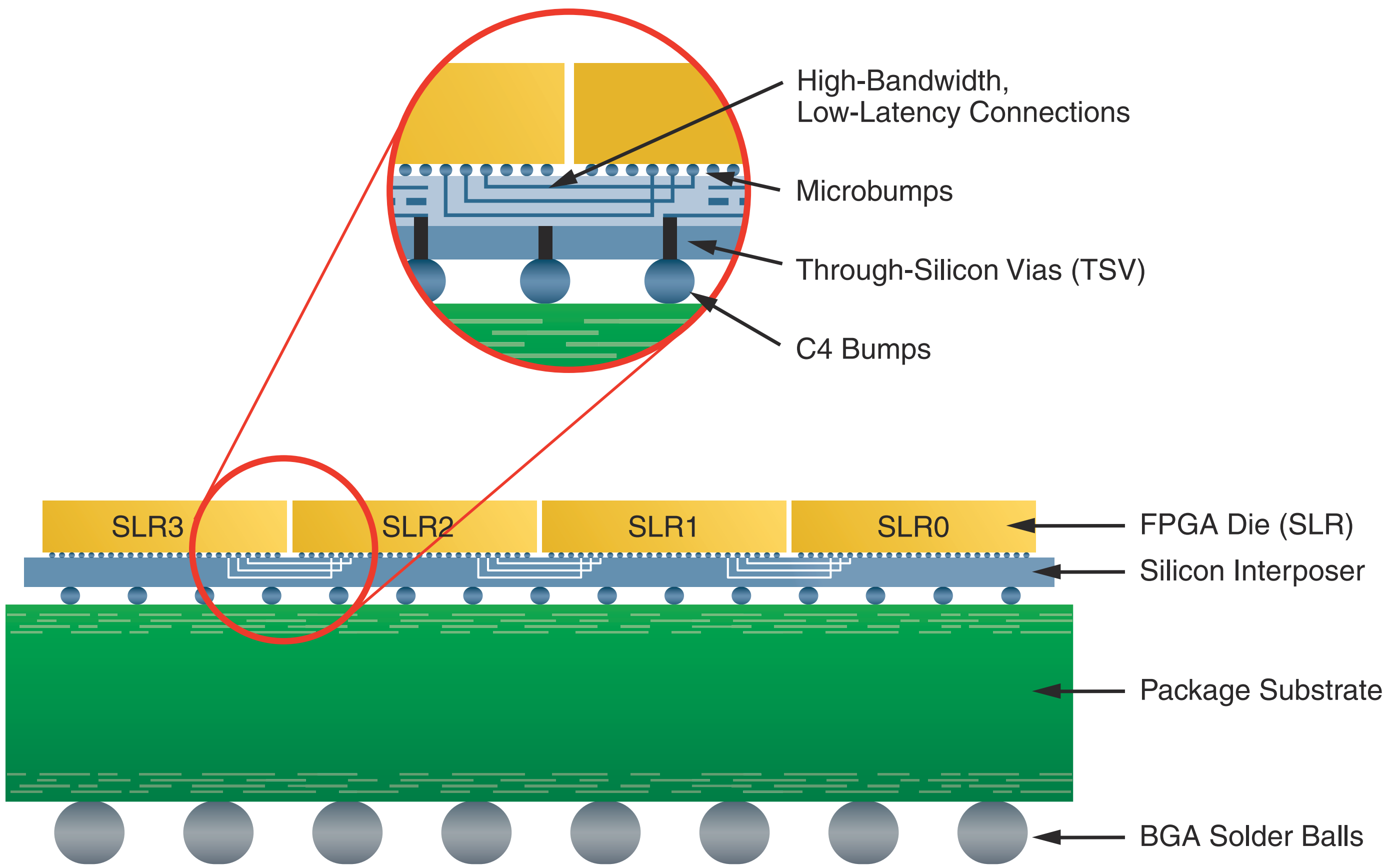
- **First implementation of Dense, 2D-Convolution and MaxPooling layer done**
  - Paper on implementation details as well as performance evaluation published: JINST **14**, P09014 (2019)

    (implementation only, assumes data already on FPGA)

- Ongoing firmware development to cope with technical details of modern large FPGAs
  - **Not monolithic chips** but several individual chips (i.e. 3 for our reference FPGA from Xilinx), *see next slide for details*
  - **Data IO** to and from FPGA via optical fibres and multi-gigabit transceivers (MGTs) **non-trivial** for our test case (different link speeds need to be handled simultaneously)

Modern FPGA: the devil is in the details …

- **Several chips connected with finite connection**
  - Potential bottleneck depending on inputs and network architecture (only ~17k inter-chip connections)



- **Data input distributed over all SLRs**, especially problematic for larger convolution layers at the start of the network
  - **Routing** via design tool (Xilinx Vivado) **becomes challenging** once resource usage increases (larger networks)

Object reconstruction (C2)

FIAS Frankfurt Institute for Advanced Studies

FIAS

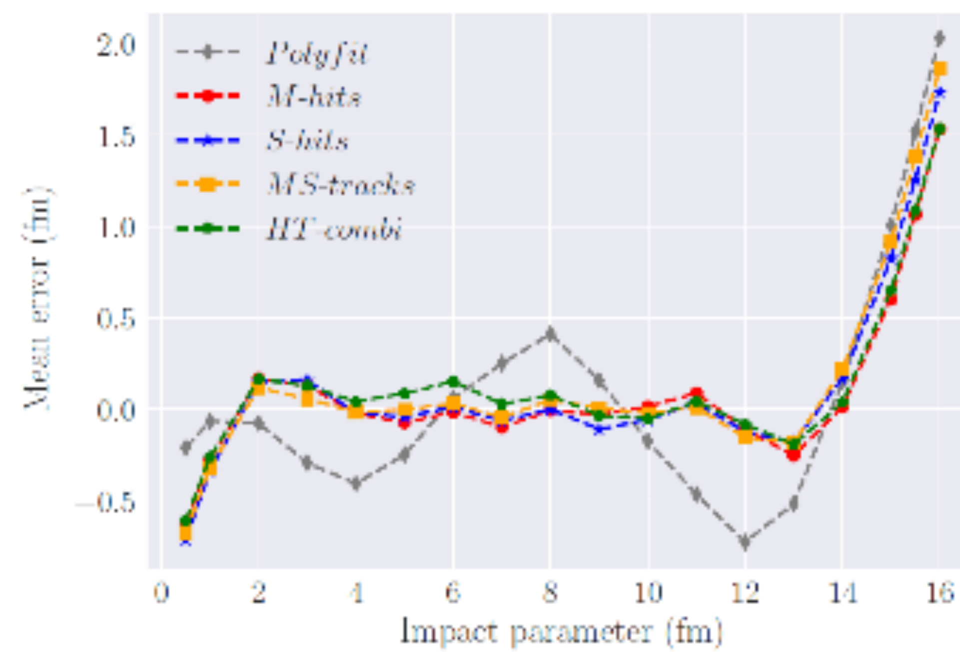
DL analysis tools for CBM (FIAS team)

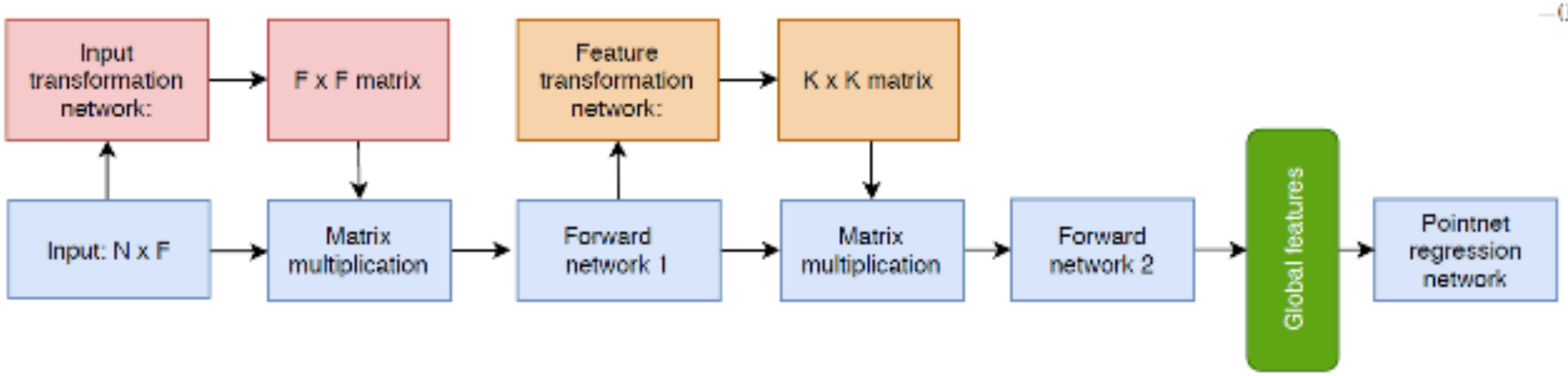
- Analysis of simulated CBM data using **PointNet** turned out to be accurate and fast

  ~O(1000) events per GPU (NVIDIA) without optimizing for speed.

- Can do centrality selection or physics identification

  - M. O. Kuttan, J. Steinheimer, K. Zhou, A. Redelbach and H. Stoecker, [arXiv:2009.01584 [hep-ph]].
  - EoS classification : In preparation



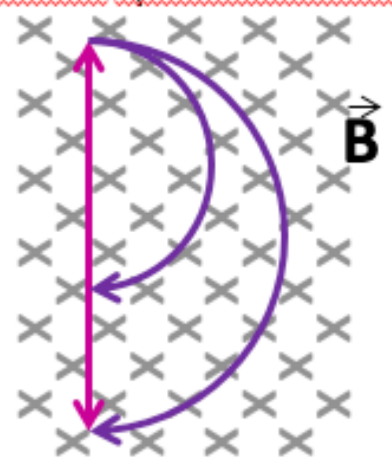


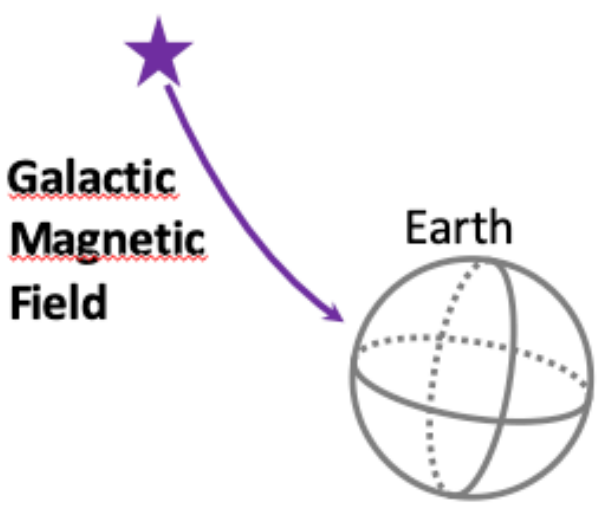
Prediction of impact parameters from unordered sets of tracks/hits

T. Bister, M. Erdmann, J. Glombitza, N. Langner, J. Schulte, M. Wirtz, arXiv:2003.13038

Patterns in cosmic ray arrival directions

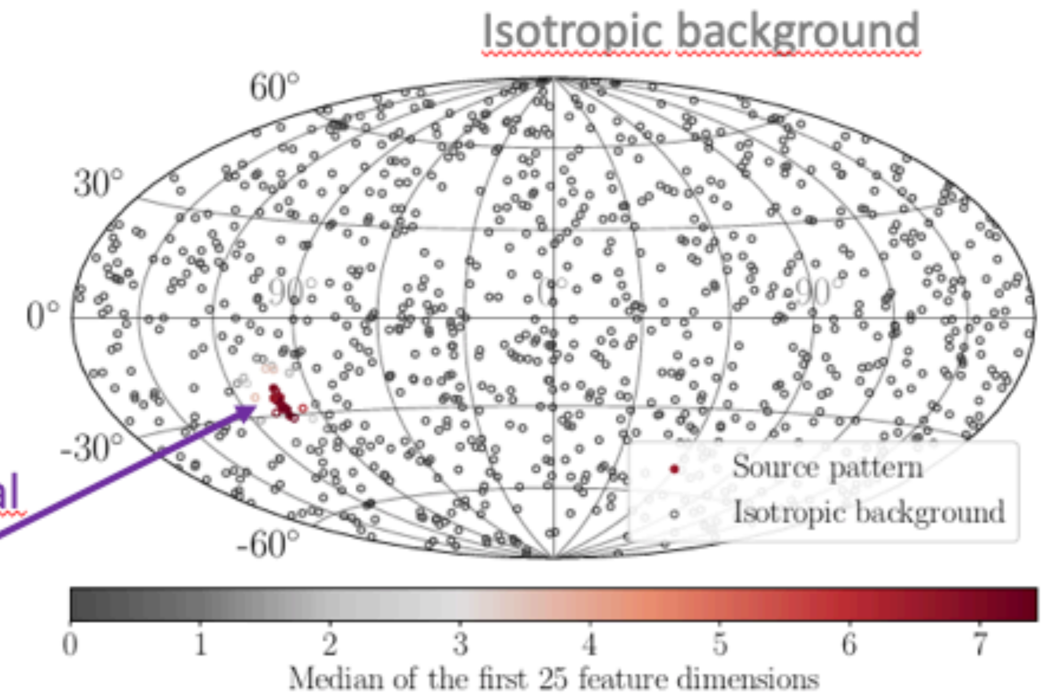
Mass spectrometer

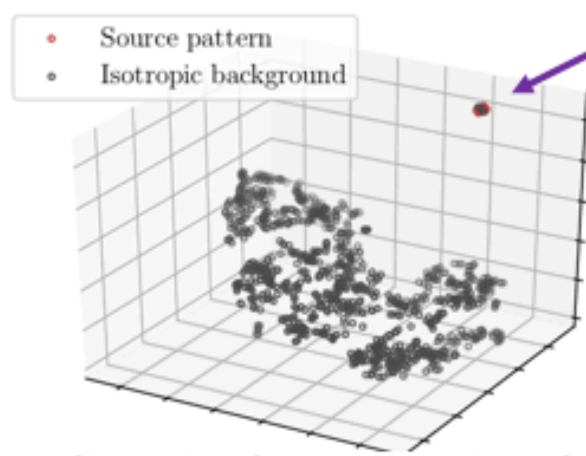




Graph network recognizes cosmic ray arrival pattern, separates it from background cosmic rays

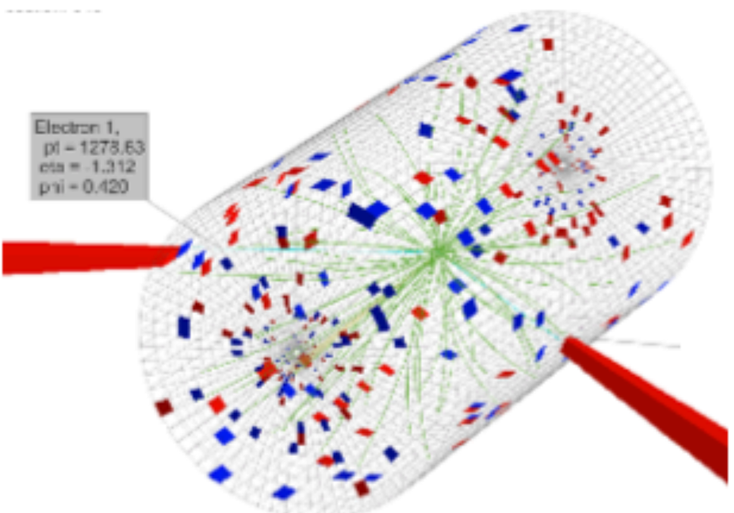
signal



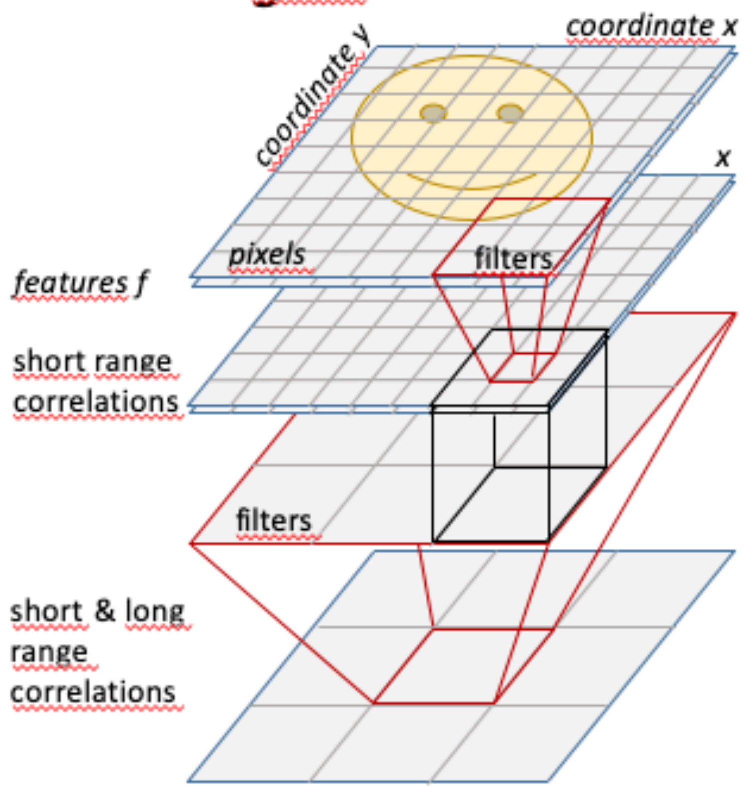


A three-dimensional representation of the final EdgeConv layer's output is created using the t-SNE technique [68].

Convolution: *Classic* versus *Graph* network

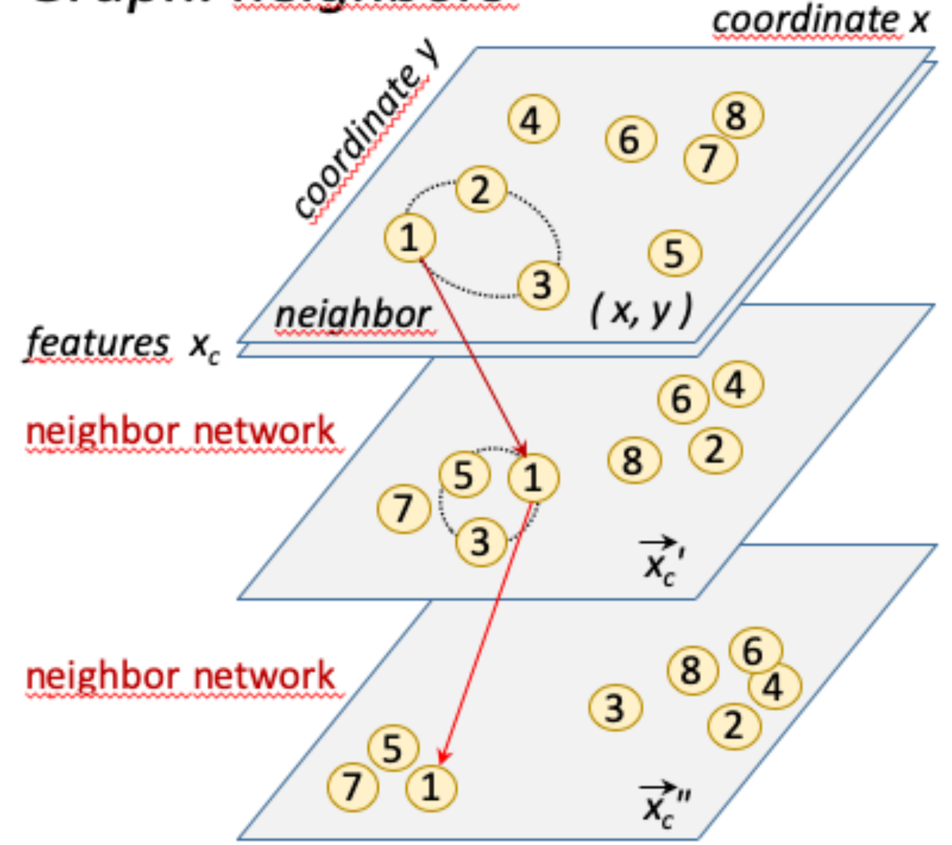


Classic: grid



- dense pixel occupation
- object identification
- analysis: single pixel contributions

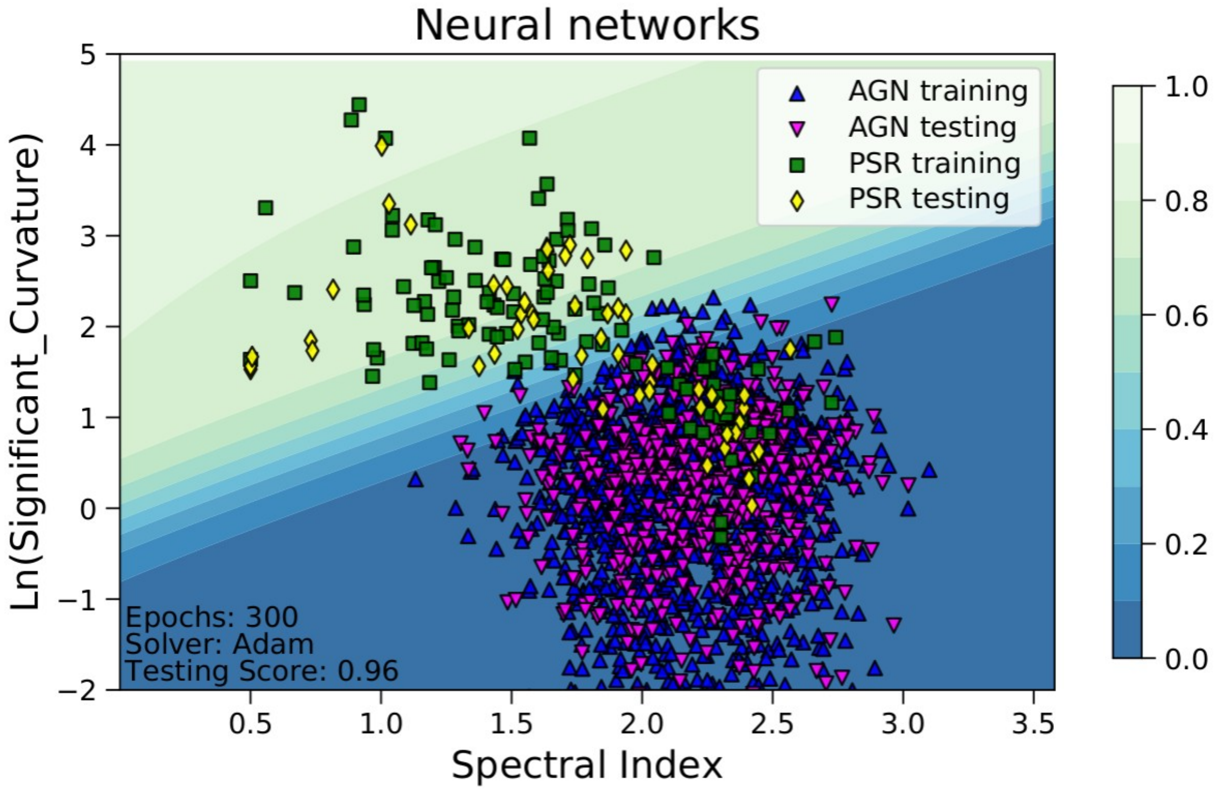
Graph: neighbors

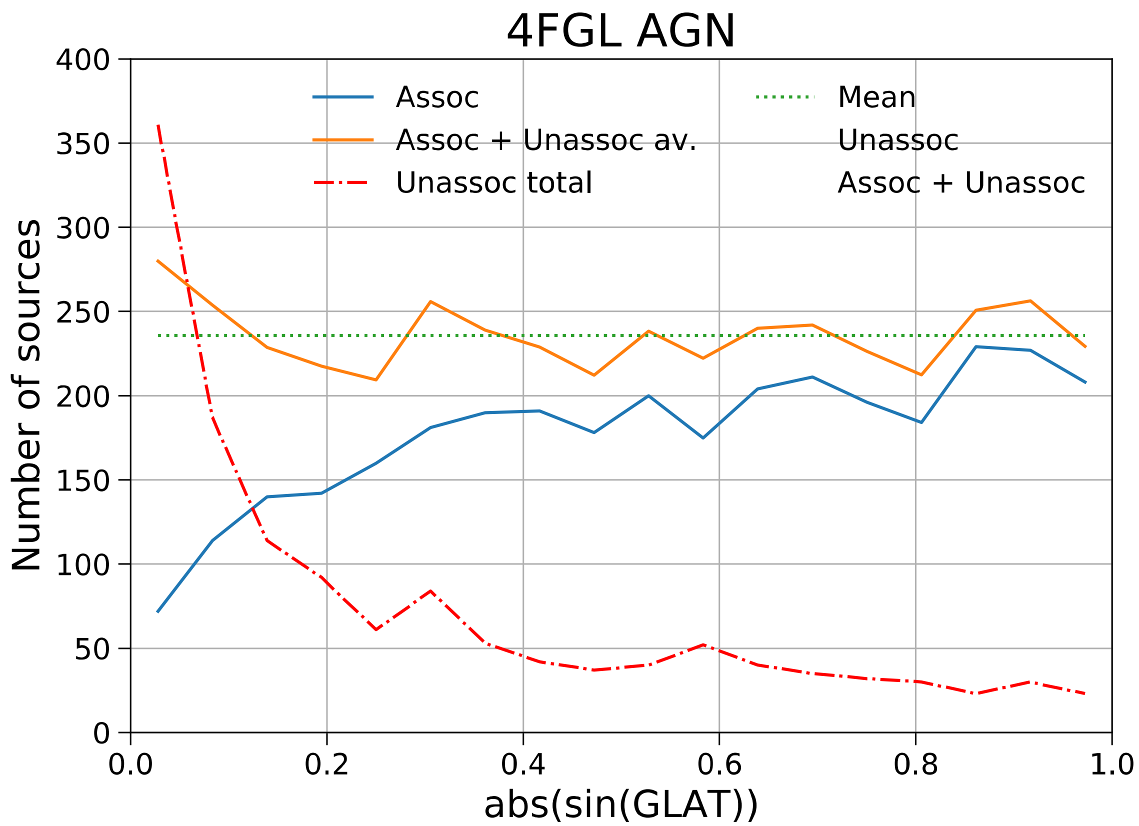


- sparse or dense neighbor occupation
- pattern recognition
- single objects 1 identification

Martin Erdmann

- Fermi LAT – gamma-ray astrophysics
  - **Aakash Bhat, Dmitry Malyshev**
  - Machine learning
    - Classification of unidentified point sources





We use associated sources to train four ML algorithms (RF, BDT, LR, NN) to classify sources into active galactic nuclei (AGNs) and pulsars.

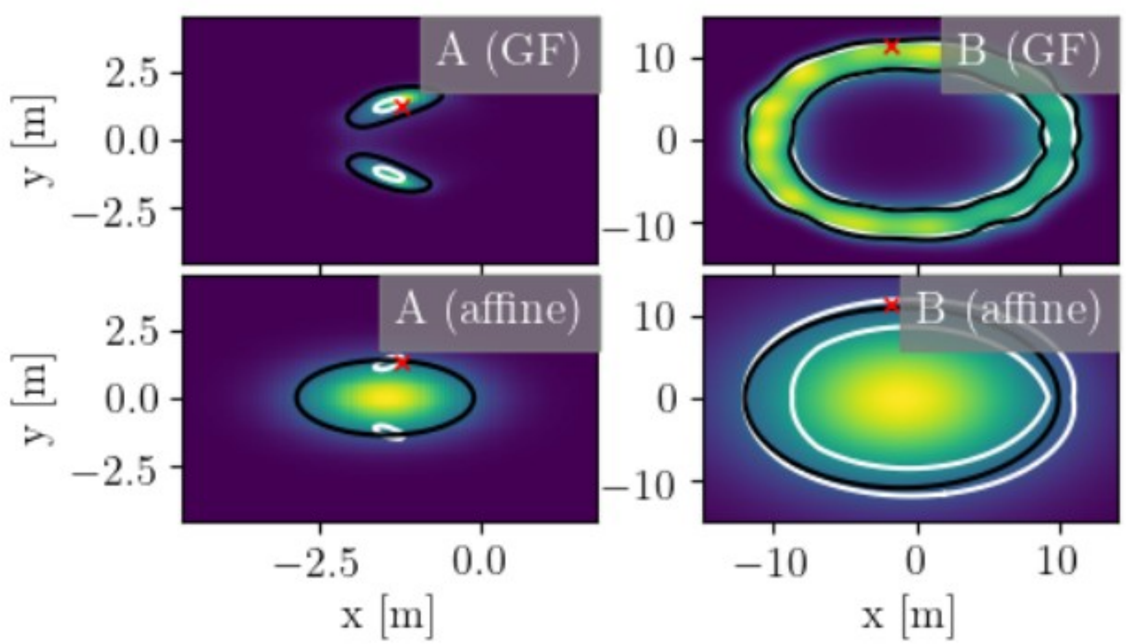
ECAP: some new results since last meeting

Normalizing flows → generalize supervised learning as approx. likelihood-free inference (2008.05825 – or see talk this meeting)
Thorsten Glüsenkamp

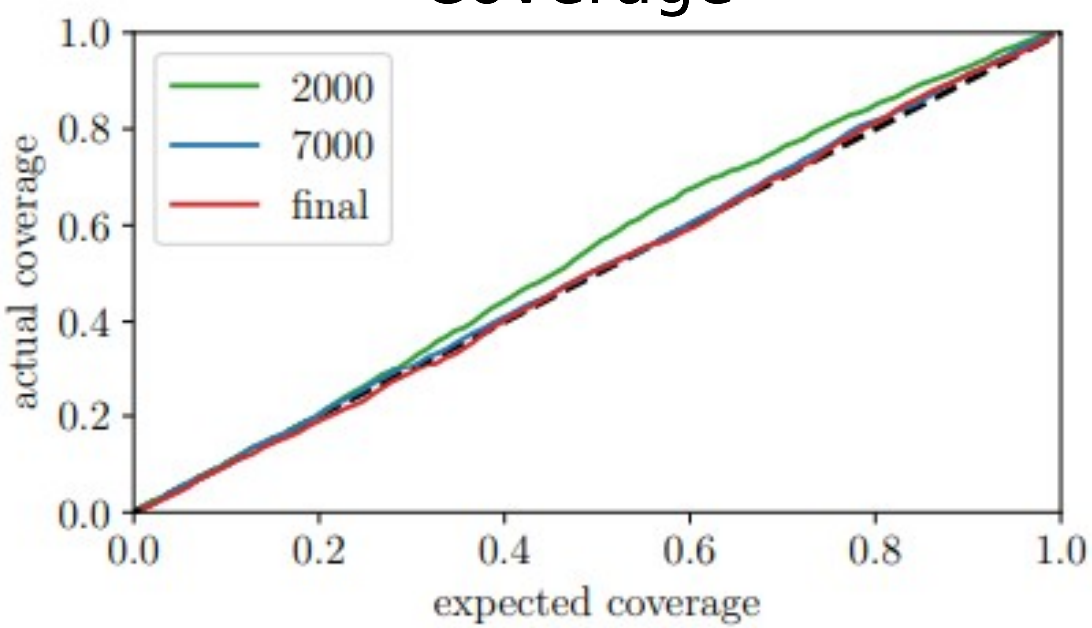
1) Systematics
2) Goodness of fit
3) Coverage

for Neural network Posterior

True Posterior (White contour)
Approx Posterior (Black contour)



Coverage



Thorsten Glüsenkamp

Classification Comparison

- ErUM domains work with a diverse set of data representations
  - Different detector geometries, different types of experiments, theory calculations…
- But: several approaches should be flexible enough:
  - Fully connected
  - 1D convolutions
  - Graphs
  - Images
  - …?

Datasets

- Top Tagging at the LHC link, Publication: 1902.09914
- Spinodal or not? link, Publication: 1906:06562
- EOSL or EOSQ link, Publication: 1910.11530
- Cosmic Airshower link
- LHC Olympics 2020 (Unsupervised anomaly detection) link

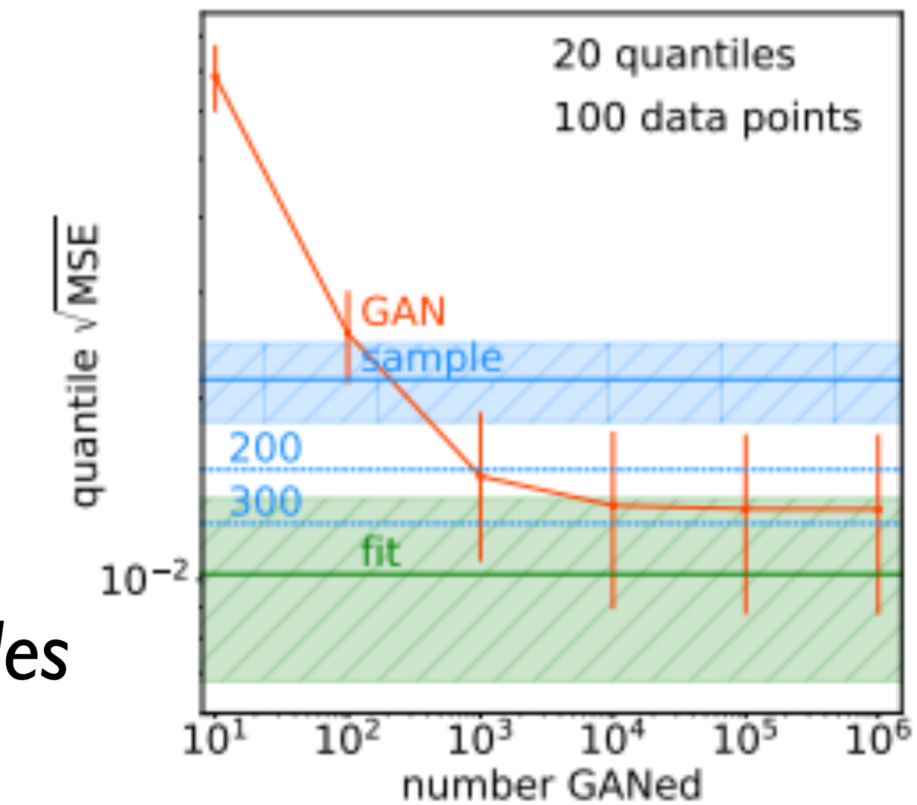
- Collecting datasets to enable cross-experiment / cross-disciplinary benchmarking of data representations and algorithms for our applications
- Focusing on classification as it allows straightforward benchmarking
- See: https://github.com/erum-data-idt/ClassifierComparison (and contact me with more datasets/cross-dataset comparisons)

Fast generation (C3)

Hamburg

- Major motivation for generative models:
  - Speed-up event generation/simulation as they are computing bottle-necks
- How?
  - Generate N events using classical approach (e.g. Geant4)
  - Train generative model (e.g. GAN)
  - Sample M events from GAN
- Only helps if amplification (M>N) possible
- Sascha will present recent result tomorrow showing that this can be achieved for simple examples

arXiv:2008.06545 - *GANplifying Event Samples*



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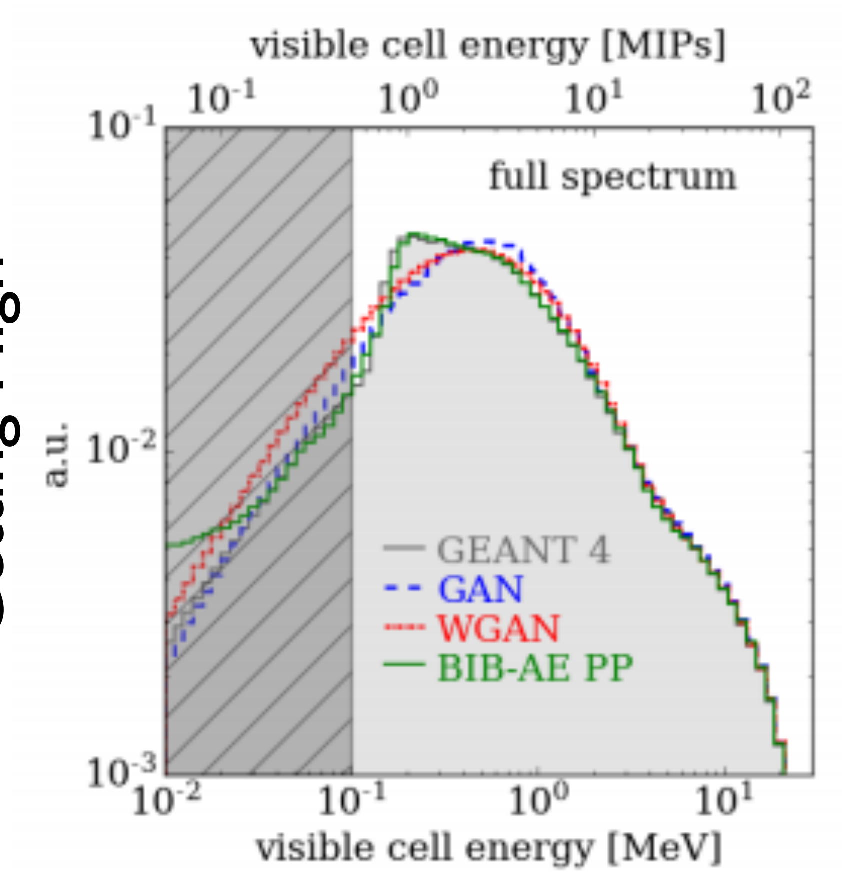
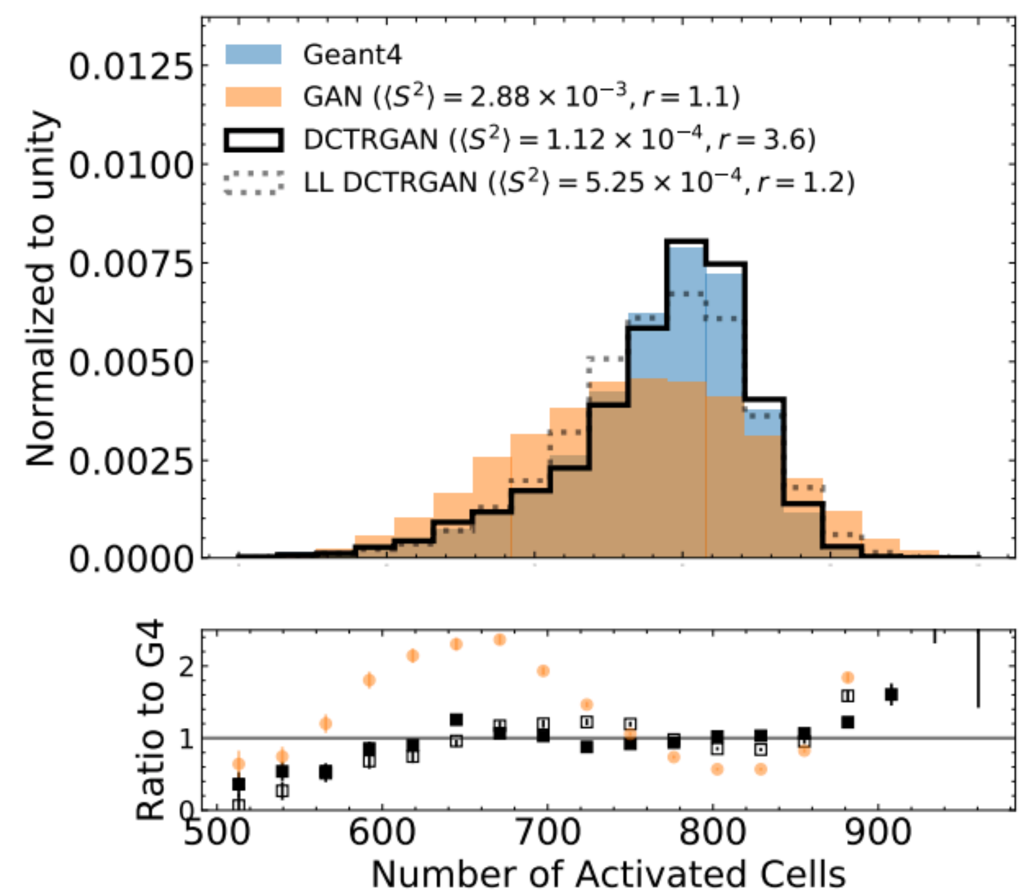
- Application: calorimeter showers for future colliders
- BIB-AE architecture achieves good fidelity
  - update by Erik in last meeting, paper out now:
    arXiv: 2005.05334 - *Getting High: High Fidelity Simulation of High Granularity Calorimeters with High Speed*
- Further improvement via event-wise re-weighting (refinement)
  - Train classifier (full simulation vs GAN output) and use to derive weights
    arXiv: 2009.03796 - *DCTRGAN: Improving the Precision of Generative Models with Reweighting*

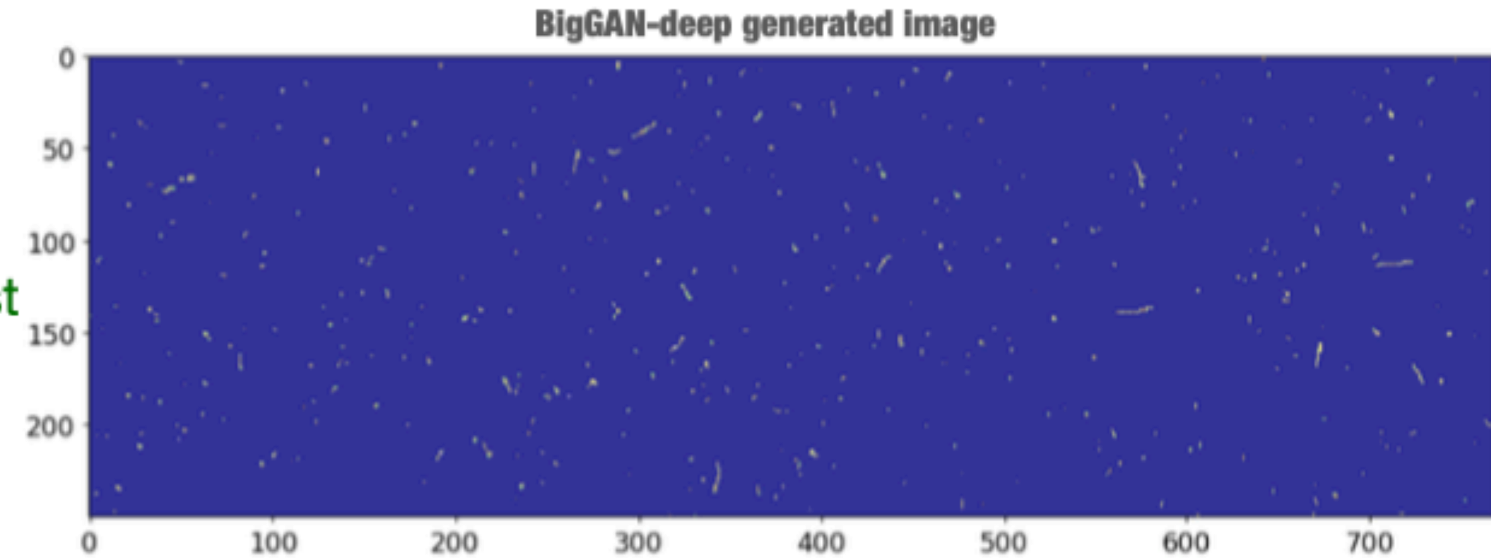
Getting High

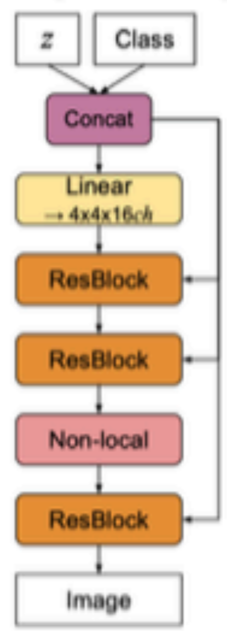




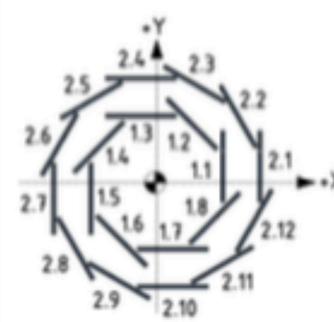
Generating PXD-bg heat-maps using GAN

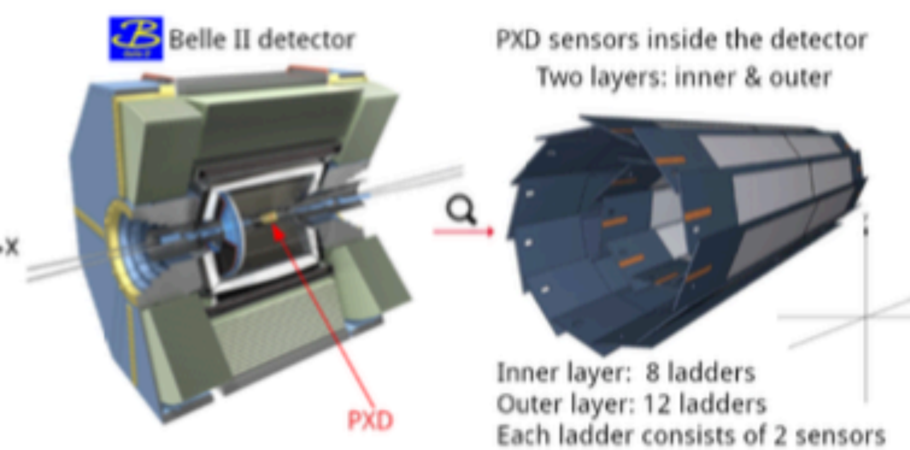
- The Pixel Vertex Detector (PXD) is the innermost semi-conductor sub-detector at Belle II.
- Detector simulation consists of both signal and background → PXD images have the highest storage consumption
- Using ***GAN*** instead of huge samples of Geant4 simulation or recorded Data.
- ☑ Initial Model: ***WGAN-gp*** New Model: ***LOGAN***
- ☑ Using *Class Conditional GAN* for increasing image fidelity and generate sensor-based images: ***BigGAN-deep***
- ☑ Validation of generated images:
  - Impact parameter resolution: *Frechet Distance*
  - Track reconstruction efficiency
- ☐ Outlook → Generate Images based on bkg type & capture correlation between layers





BigGAN-deep



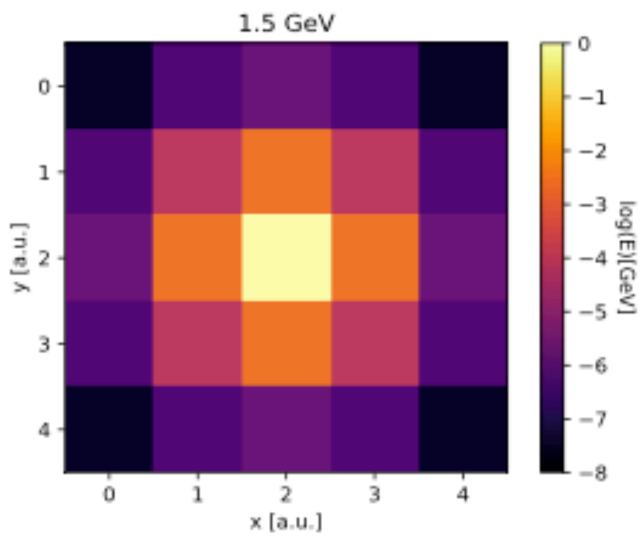


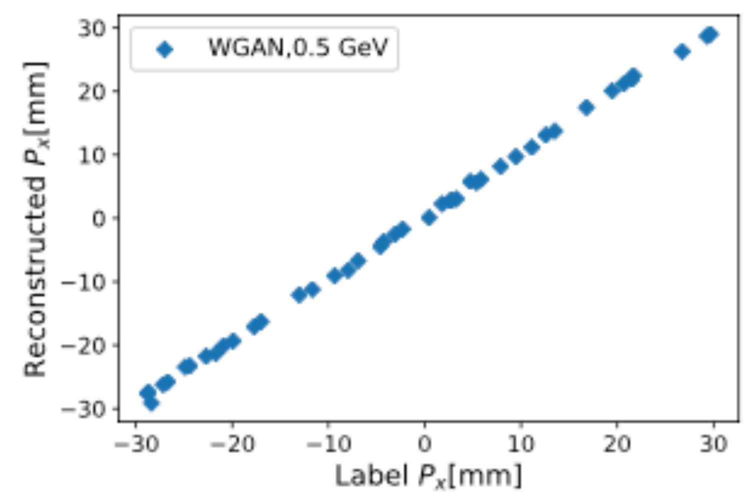
Fast Simulation of Particle Showers

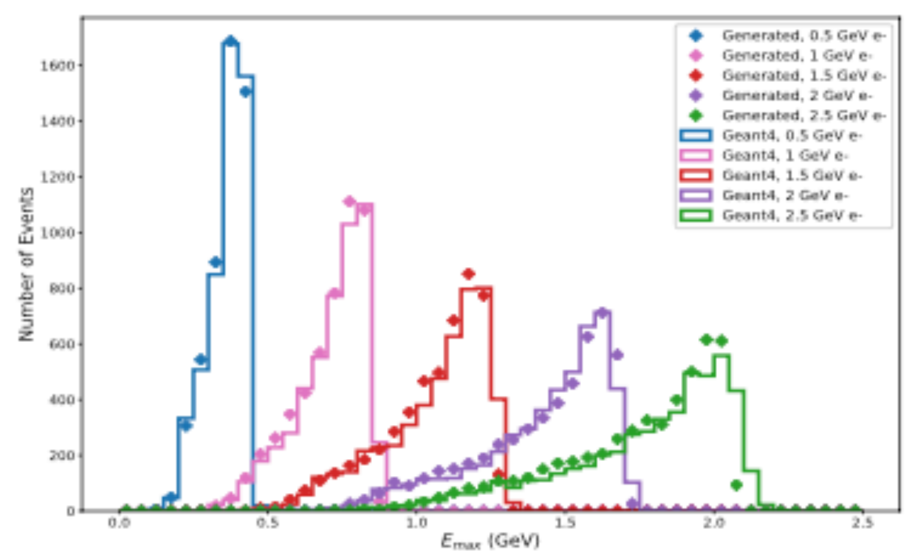
Wasserstein GAN →

$$L_{Critic} = E[C(G(z))] - E[C(x)] + \lambda E[(\| \nabla_{\hat{x}} C(\hat{x}) \|_2 - 1)^2]$$

$$L_{Generator} = -E[C(G(z))]$$



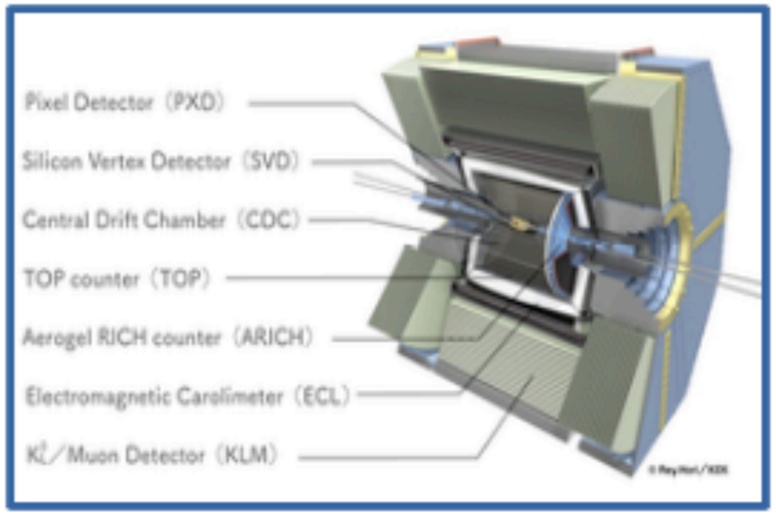


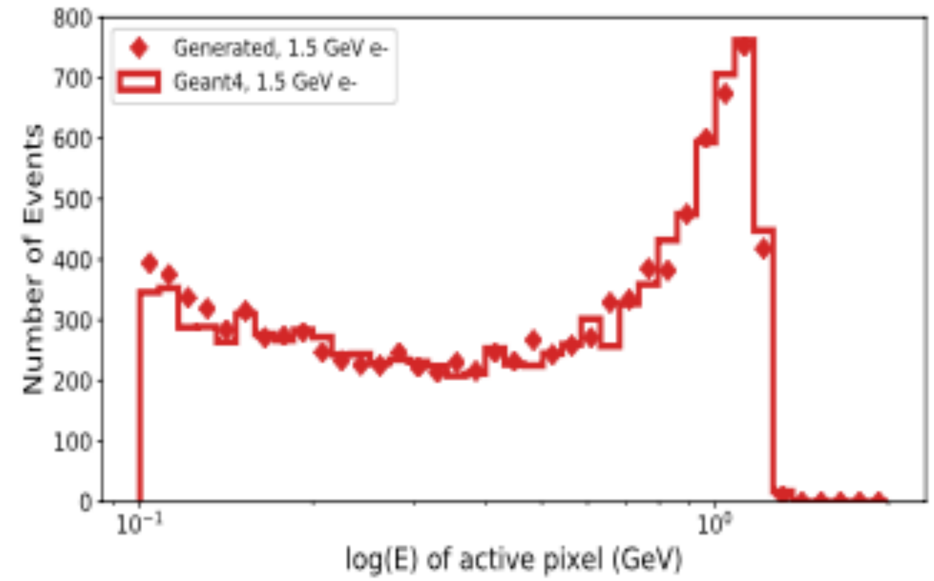


Jubna Jabbar

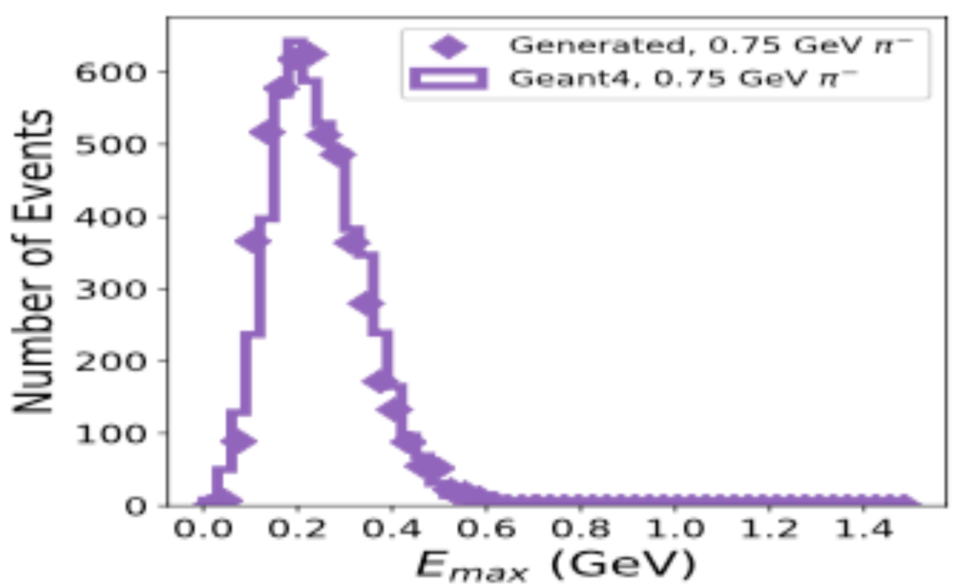
Karlsruher Institut für Technologie

Testing the model for electron showers in Belle II ECL crystals





Hadronic shower simulation

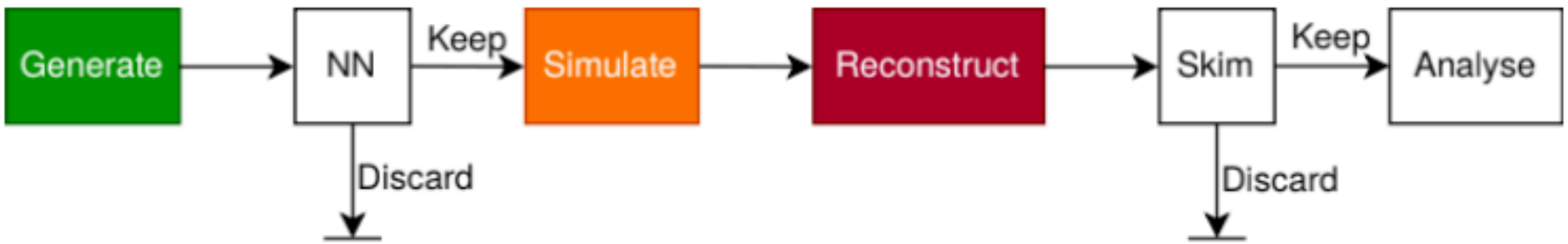


VAE-GAN

Jubna Jabbar

SmartBKG project at LMU

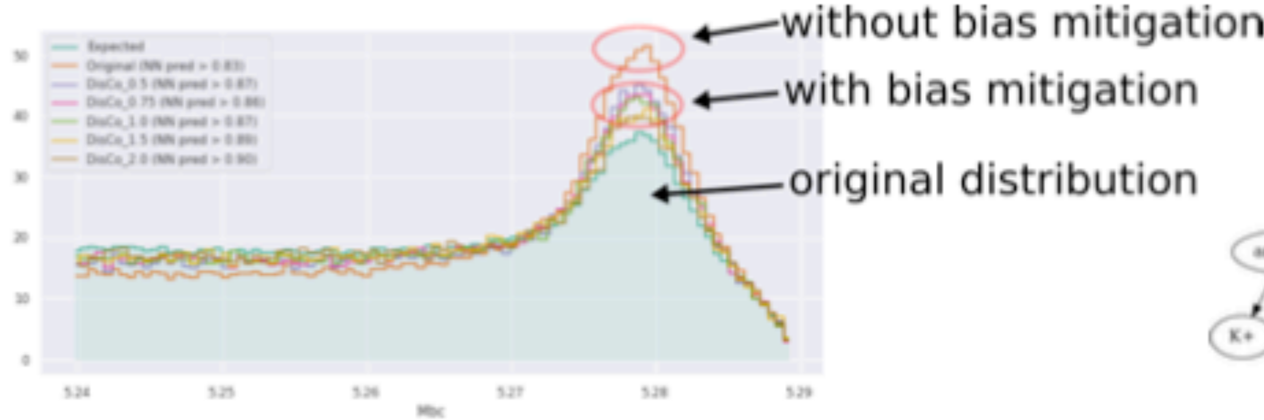
Try to filter Events already before expensive detector simulation and reconstruction



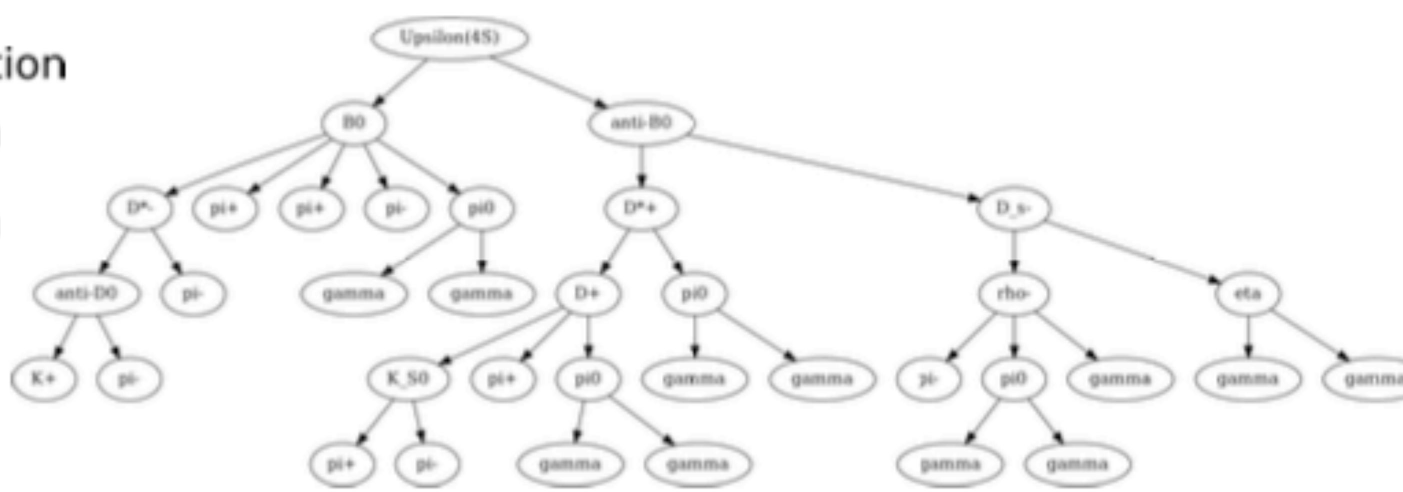
- Architectures based on graph convolutions have good performance
- Studied mitigation of bias due to false negatives

  ➔ distance correlation term in loss function

  (decorrelate classifier output from observables)



Inputs: Event decay tree
+ particle features (generator level)



- Preparing dataset for Classifier comparison

Closing

Summary

- Range of activities in ErUM-data C
- Algorithms suited to our data-structures
  - New results and convergence on similar approaches
  - New statistical tools for data analysis
- Machine learning close to hardware
  - Implementation of several key architectures done
  - The devil is in the details..
- Fast generative models
  - Many applications
  - First hints at possible amplification of statistics

Look forward to detailed updates tomorrow

Agenda for Tomorrow Session D+C

D	09:00	**15 - Status of ACTS Deployment at FASER**	*Tobias Boeckh*
D		**16 - Status of Belle II ACTS Activities**	*Ralf Farkas*
C		**17 - Impact paremeter for heavy ion collisions with a PointNet architecture**	*Manjunath Omana Kuttan*
C	10:00	**24 - Identification of Cosmic Rays from Sources using Dynamic Graph Convolutional Neural Networks**	*Niklas Langner*
C		**Short coffee break**	
C		**18 - Using Generative Networks to amplify statistics**	*Sascha Diefenbacher*
C	11:00	**19 - Flow-based networks and their benefits for high-energy physics**	*Thorsten Glüsenkamp*
C		**20 - Fast simulation of particle showers**	*Jabbar Jubna*
C		**21 - Selective Background Monte Carlo simulation with deep learning**	*Nikolai Hartmann*
C	12:00	**23 - PXD background image generation using GANs**	*Hosein Hashemi*

Just updated!!!