Real-time data compression with Bicephalous Convolutional Auto-Encoder

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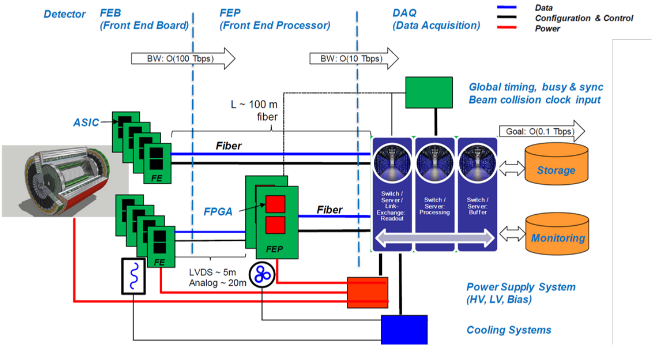
Sept. 9, 2021

Introduction

Major challenges of Electron-Ion Collision streaming data acquisition



EIC CDR Fig. 8.27: Diagram of the detector readout and DAQ system [Ref. "EIC readout overview" by Fernando Barbosa]

- EIC signal data rate is low and we aim to stream readout all variety of collision signal
- Experiment data may be noisy and filled with background hits
- Experiment data can be too large and expensive to fit in persistent storage limit

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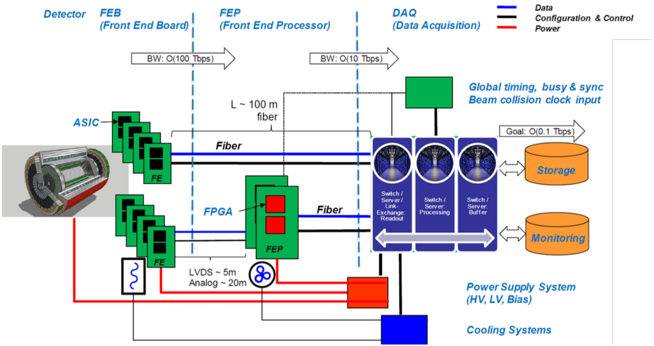

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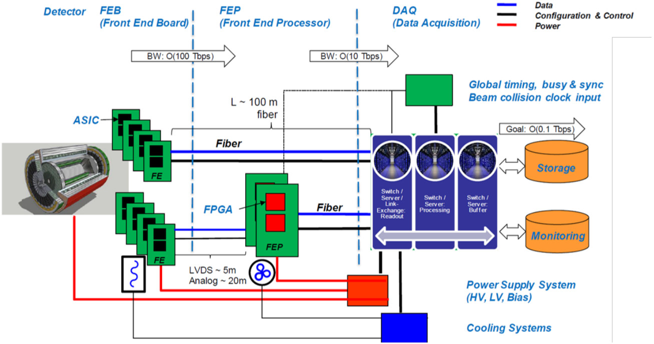

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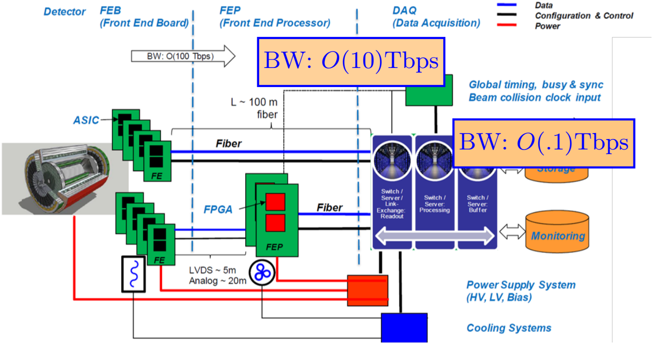

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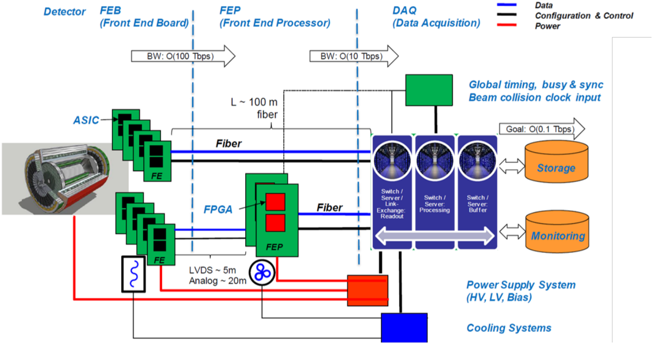

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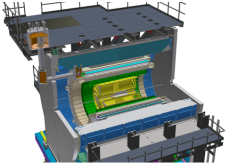
Goal

Using machine learning for **data compression** and **noise filtering**.

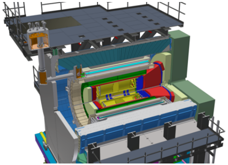
Introduction

Time projection chamber (TPC) data

- Time projection chamber is a popular choice of main tracking detector for both RHIC and EIC experiments
  - Using the sPHENIX TPC data model for this study: high data rate and well modeled device
  - Algorithm would be applicable for EIC tracker and calorimeter too
- **Compression**: TPC data dominates the data volume
- **Noise filtering**: TPC data may contain a high amount of noise ($> 50\%$) from the experiment background
- **High throughput** to match TPC data taking



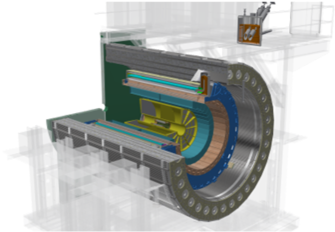
sPHENIX @ RHIC, 2023-2025
sPHENIX Technical Design Report



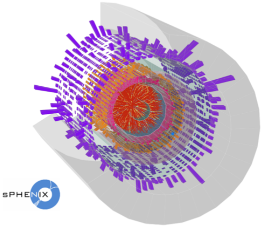
One of the EIC detector concepts, ∼2030
arXiv:1402.1209

Introduction

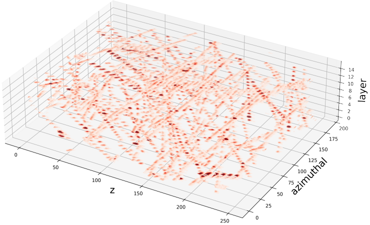
TPC data in this study



Detector model



Detector simulation



An example of
TPC data frame

Preparing for the toughest

In this study, we use the 10% central Au + Au collision with 170kHz pile up, which is busiest event in sPHENIX.

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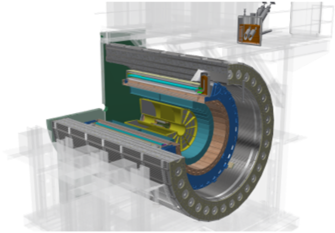

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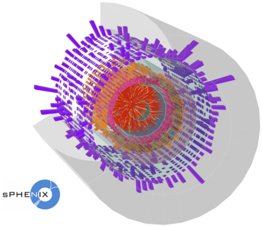

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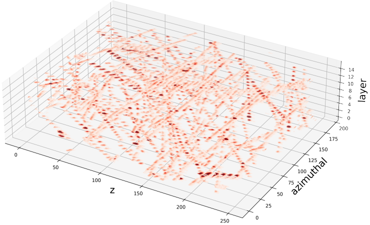

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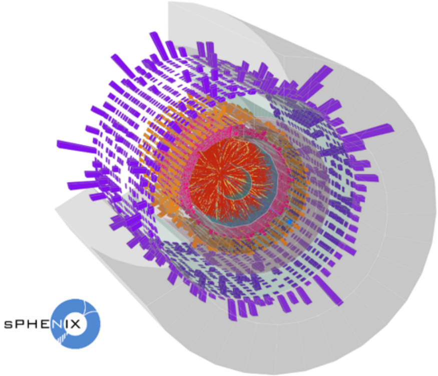
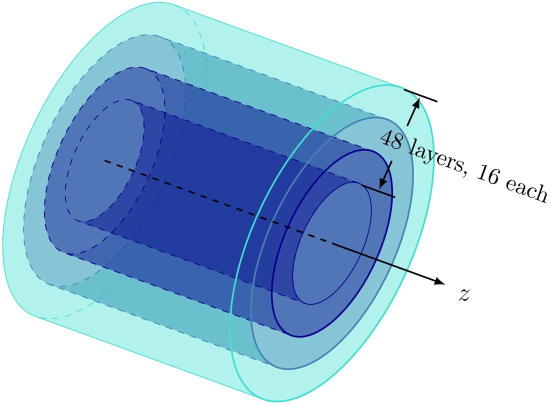
Time projection chamber zoom-in





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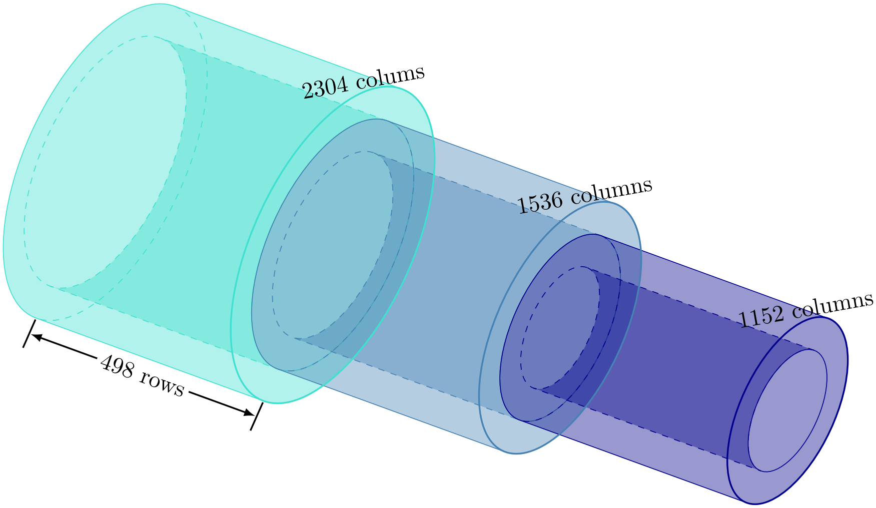

The Amount of Data Generated by TPC

- **Data format**: 10-bit integer (ADC value range $\in [0, 1023]$)
- **Number of voxels**: (azimuth $\times$ z $\times$ layer)
  - Outer layer group: $2304 \times 498 \times 16 \approx 18M$;
  - Middle layer group: $1536 \times 498 \times 16 \approx 12M$;
  - Inner layer group: $1152 \times 498 \times 16 \approx 9M$
- **Digitization frequency**: 20MHz;
  Frame Frequency: 80KHz

Uncompressed data rate: ~30 Tera bits per second

Average compressed data rate via SAMPA ASIC: $\sim$ 2Tbps

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Lossy Compression Algorithms

There are many existing compression algorithms designed for simulation-heavy scientific data represented by dense matrices of high-precision floating-point values.

- SZ: Error-bounded lossy compressor for HPC data
  https://github.com/szcompressor/SZ
- ZFP: Compressor for integer and floating-point data stored in multidimensional arrays
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- MGARD: MultiGrid adaptive reduction of data
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Problems with existing compressors

Hand-crafted and manually-tuned to suit data, missing learnable noise filtering.

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Convolutional Neural Encoder

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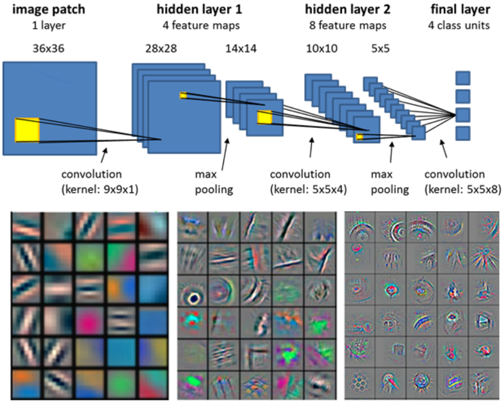
- Convolutional neural network
  (an NN architecture specialized in processing high volume image data)
- Auto encoder
  (an NN encoder learns its own encoding rule with the help from an NN decoder)



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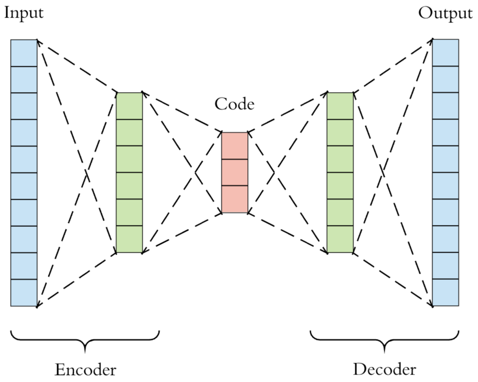

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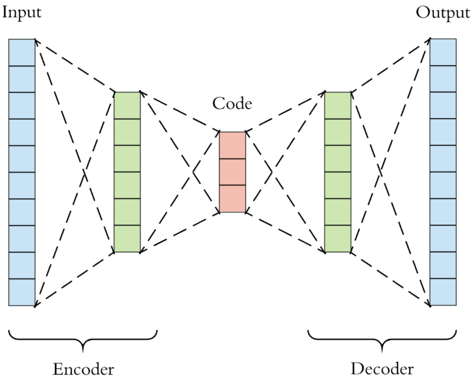
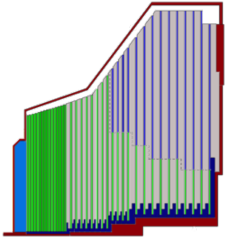


Desirable properties of a neural encoder

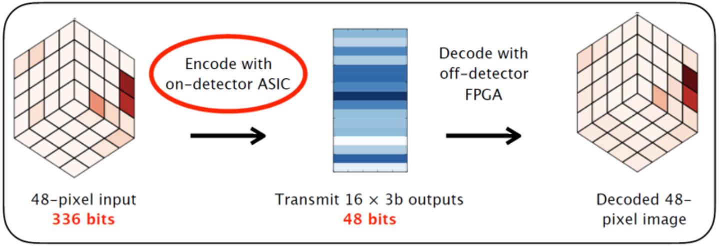
Data-driven coding rule to optimize domain specific tasks, such as noise filtering.

Example of on-going auto-encoder study in modern data acquisition

Auto-encode evaluated for on-detector data compression for CMS HGC
[Reference to talk: https://indico.fnal.gov/event/46746/contributions/210450/]



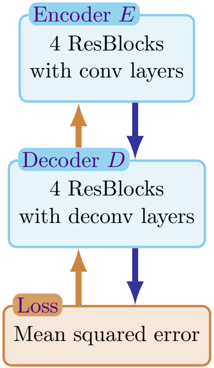
Compact Muon Solenoid High-Granularity Calorimeter

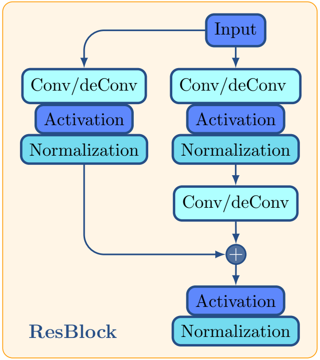


Proposed data flow with auto-encoder on application-specific integrated circuit

Convolutional Neural Encoder

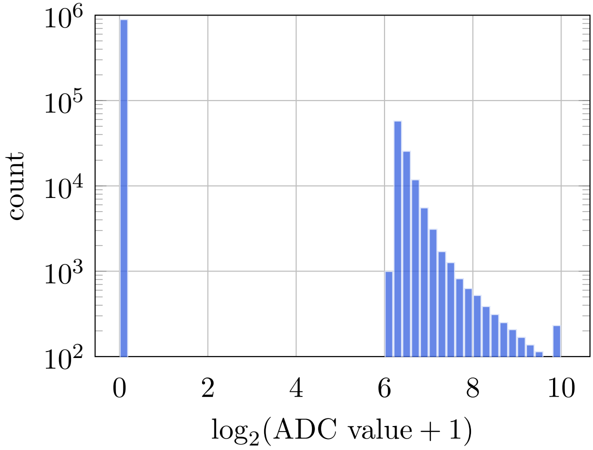
A basic idea





Convolutional Neural Encoder

Problem with the basic idea



The distribution:

- is bi-modal
- is unbalanced
- is skewed (having a sharp edge at 6)
- has a long and slender tail

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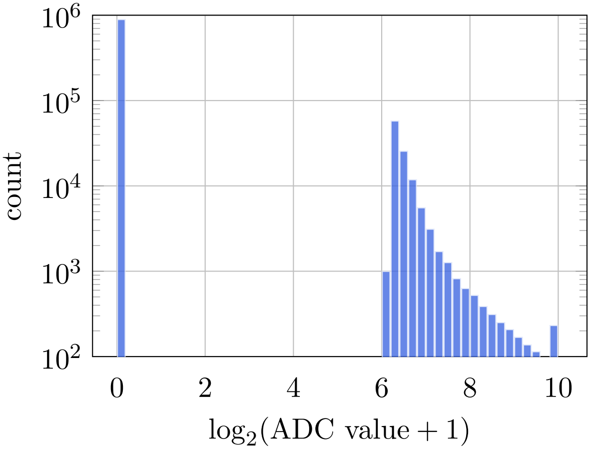

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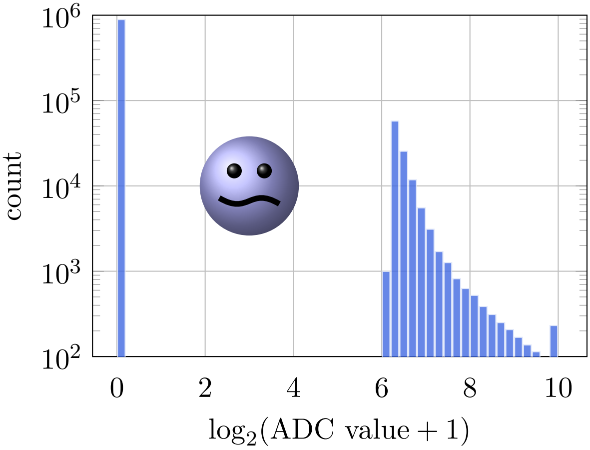

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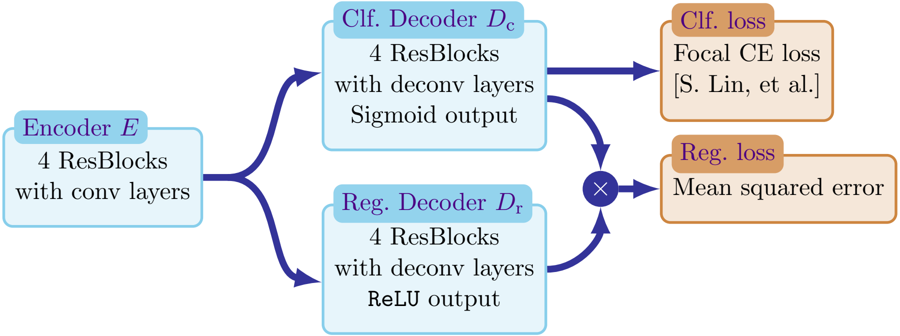
Bicephalous Convolutional Neural Encoder

Two heads is better than one



- Classification decoder D_c learns to recognize truth signal
- Regression decoder D_r learns to approximate the value of truth signal
- Decompressed data = regression masked by classification

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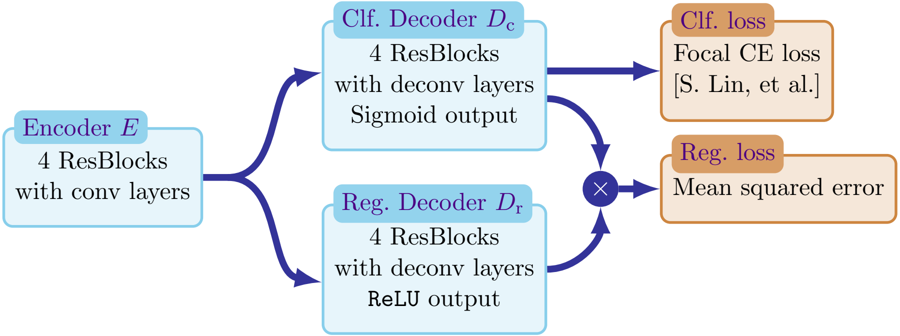

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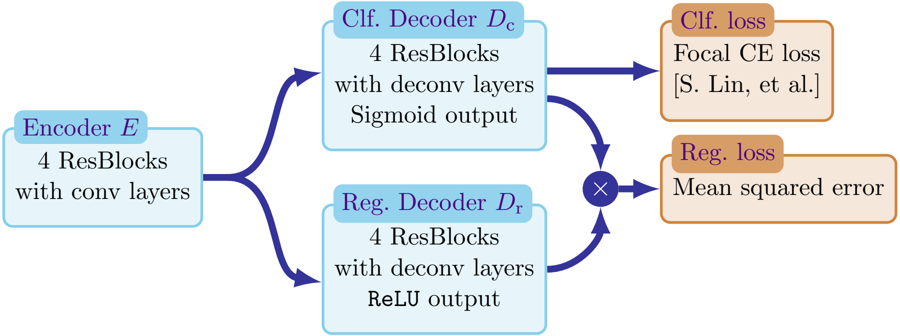

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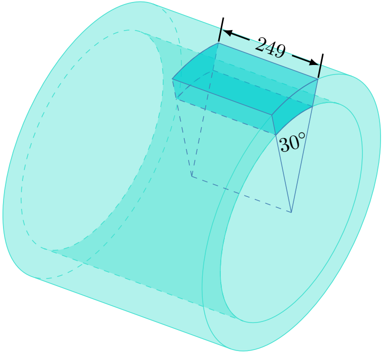
Input

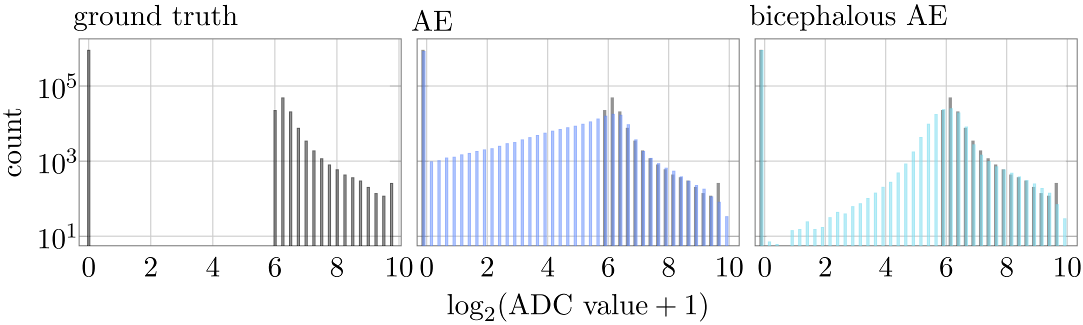
- a 30° degree sector along the azimuth direction (192 columns for the outer layer group)
- a half the z-direction (249 rows)
- one layer group (16 layers)



Results I: AE v.s. Bicephalous AE

Compression ratio is 1 : 27

(1 : 3 for SAMPA ASIC for this busiest event)

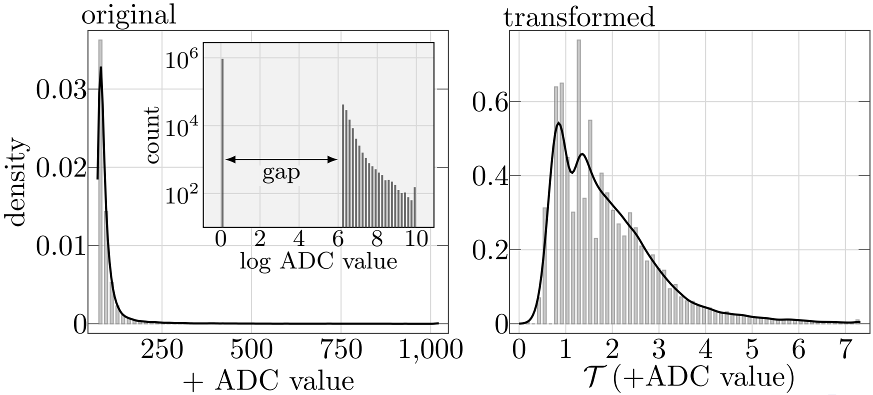


A Missing Ingredient – Input Transform

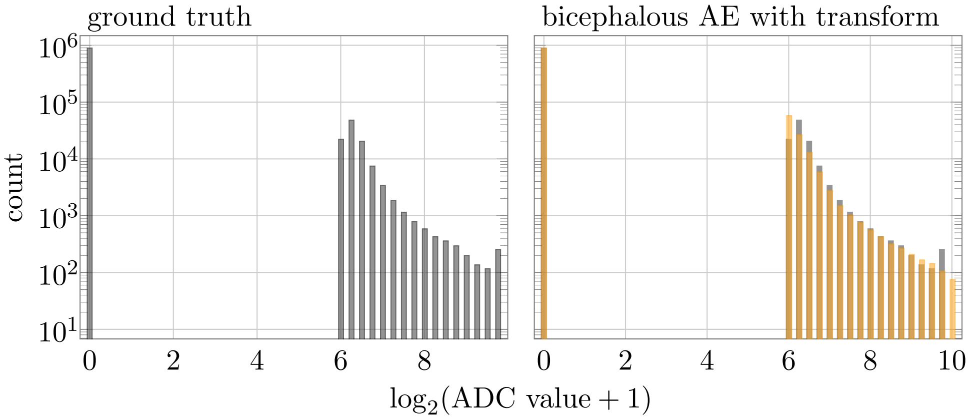
borrowed an idea from [Y. Alanazi, et al.]

$$\text{Input transform: } \mathcal{T}(x) = \log(x-64)/6, \qquad x > 64$$

$$\text{Inverse transform: } \mathcal{T}^{-1}(y) = 64 + \exp(6y), \qquad x \in \mathbb{R}$$



Results II. Bicephalous AE with Input Transform

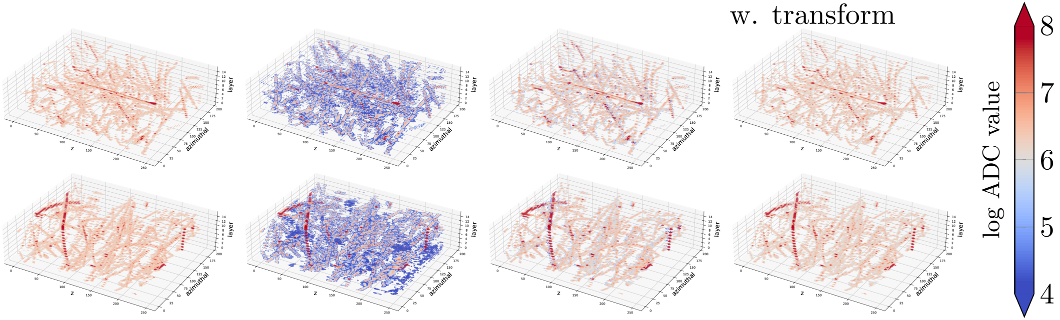


Result III. Ablation Study

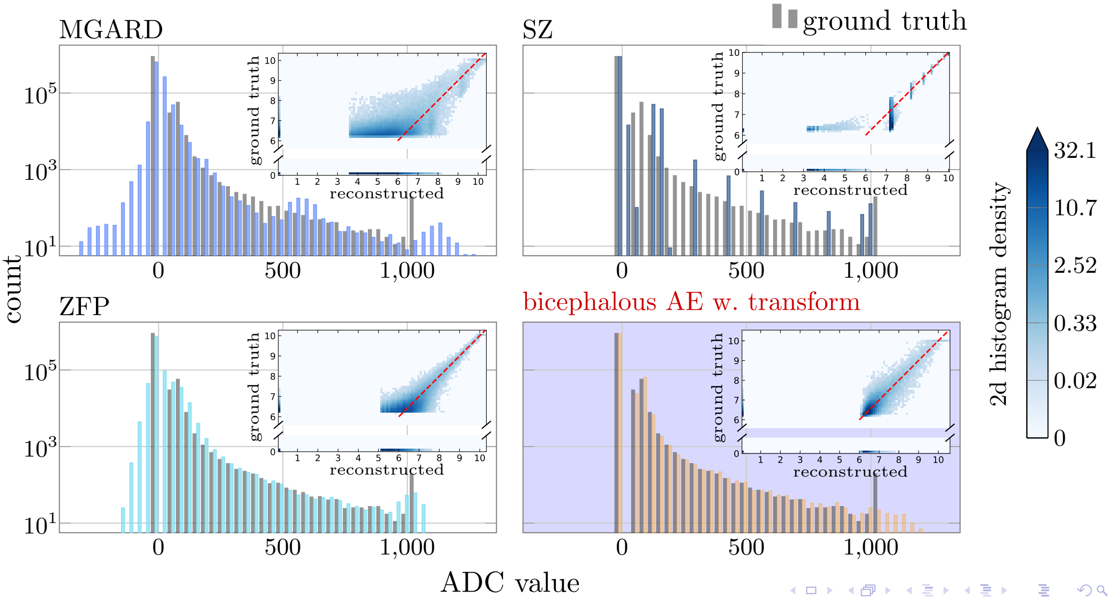
ground truth | AE | bicephalous AE | bicephalous AE w. transform

example 1

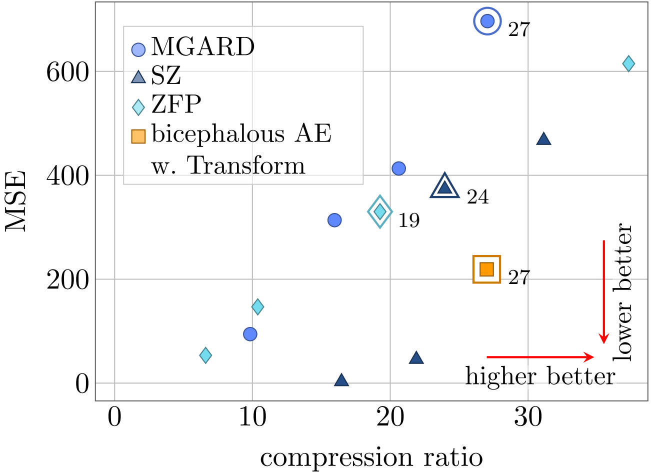
example 2



Result IV-i. Comparing with Existing Compression Algorithms



Result IV-ii. Comparing with Existing Compression Algorithms



Result V. Metrics Summary

Table: Performance comparison

	Compr. ratio↑	MSE↓	log MAE↓	PSNR↑
MGARD	**27**	626.28	1.213	3.223
SZ	24	369.69	0.302	3.452
ZFP	19	219.48	0.267	3.678
AE	**27**	227.61	0.349	3.703
Bicephalous AE	**27**	230.59	0.193	3.706
Bicephalous AE w. Transform	**27**	**218.33**	**0.185**	**3.724**

Summary and Future Direction

- Test auto-encoder-based compression and noise filtering network on highest occupancy TPC data.
- Reach $1:27$ compression ratio.
- Future directions:
  - Integrating simulation ground truth into the training to improve noise rejection.
  - Working well for downstream applications (for example: clustering and tracking efficiency and position resolution)
  - Data acquisition hardware integration

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