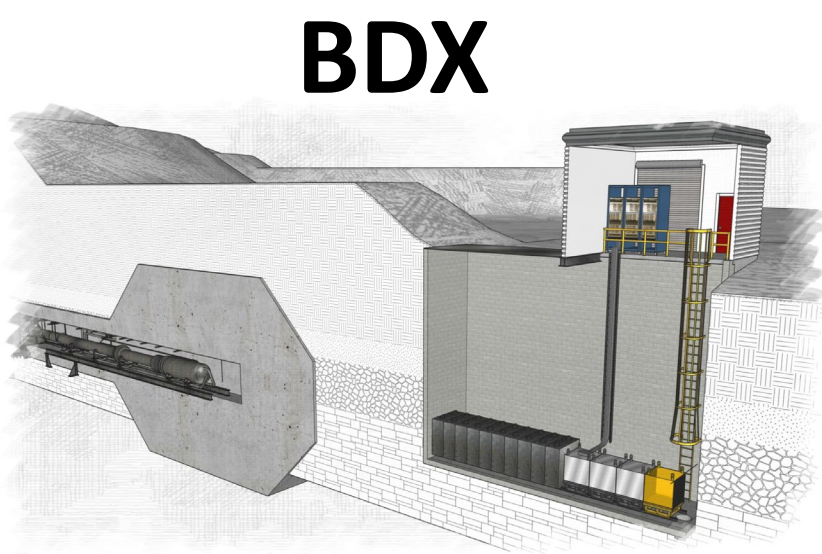


Next Generation of Experiments

Streaming Readout data acquisition is emerging as key paradigm for high-luminosity nuclear and particle physics experiments. This approach has been adopted by several future experiments such as:

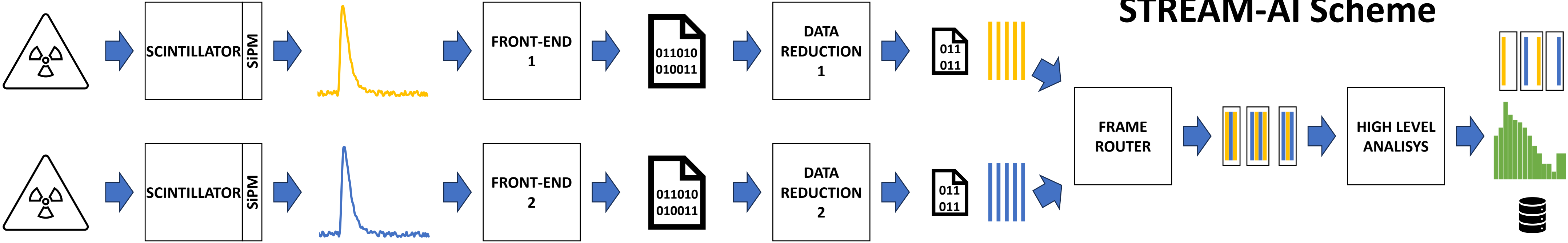
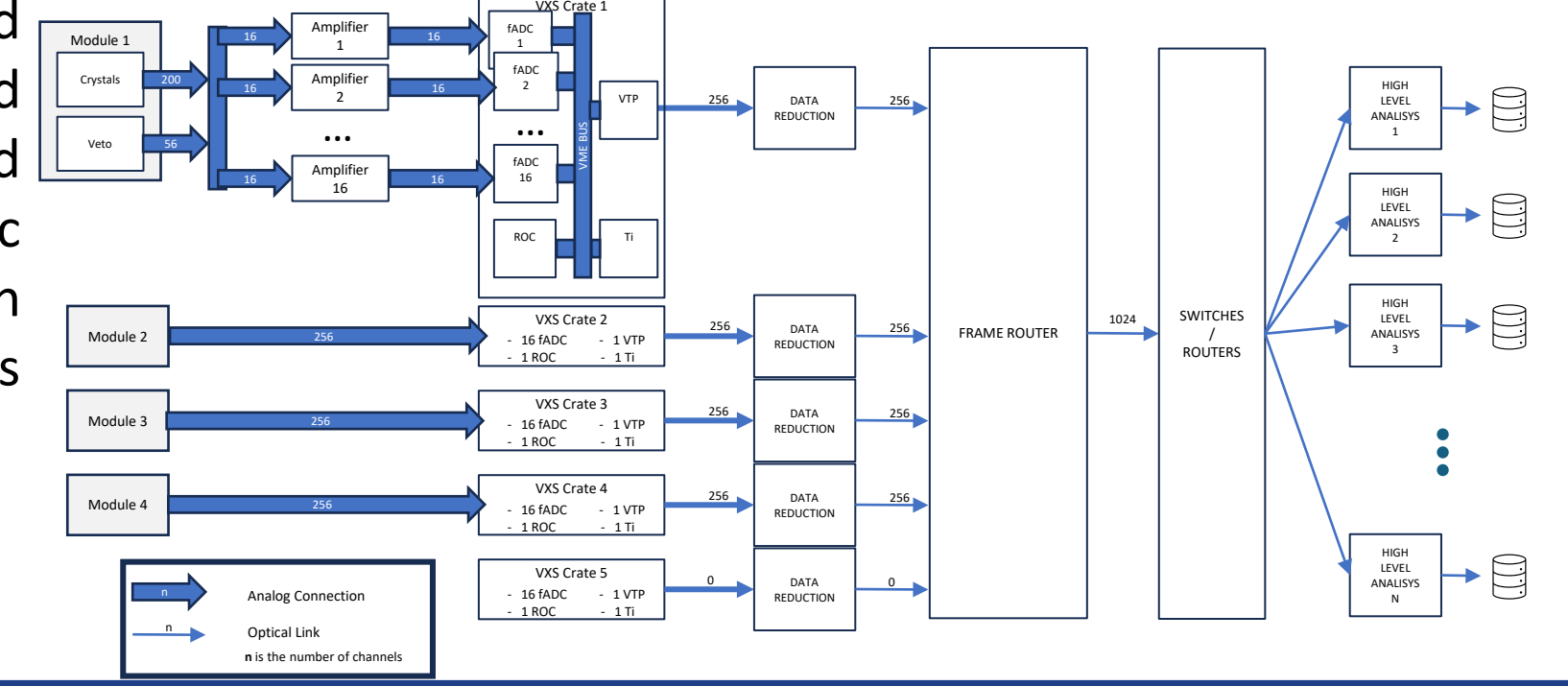


BDX

At Jefferson Laboratory, SRO architectures based on distributed microservices are being developed and validated through dedicated testbed activities under realistic operating conditions. BDX will soon start data collection with this framework.

Fully optimized and distributed often not available for testing

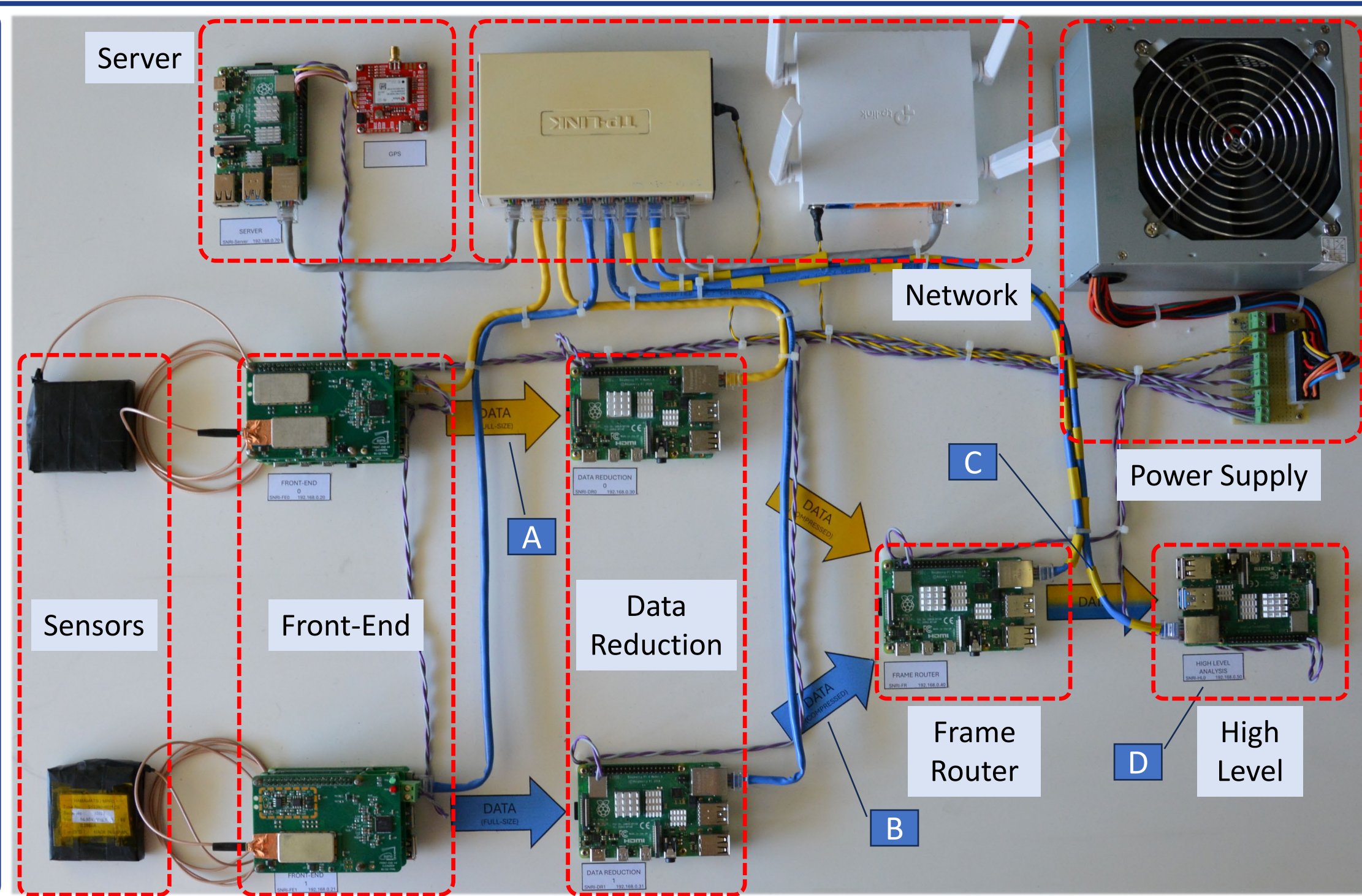
SRO DAQ (BDX case)



Educational Goals

- General concept of SRO
 - Architecture
 - Functionality
 - Bottleneck
- Required nodes in a SRO system
 - Front-end
 - Data reduction
 - Frame Routing
 - High level analysis
- Functionality of each nodes
 - Characteristics
 - Algorithm

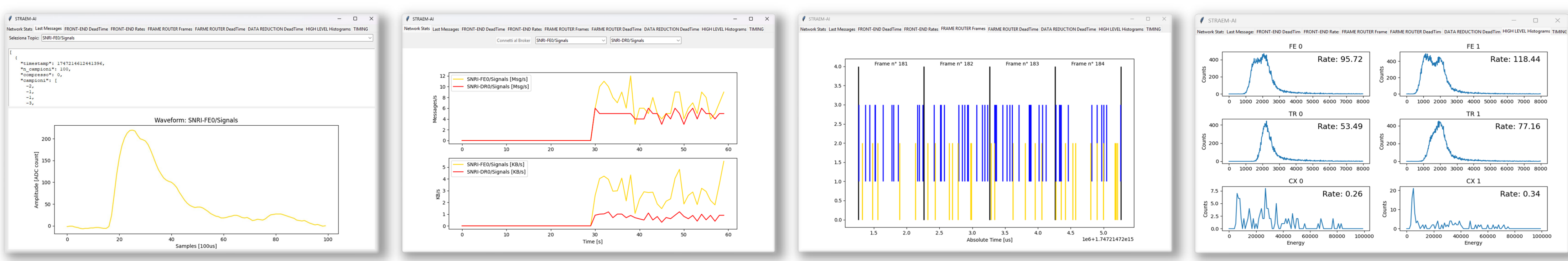
Easy to understand and always available



Research Goals

- Easy testbench for new ideas
 - AI based algorithm
 - Advance signal filtering
 - Advance Triggering system
 - Innovative Routing algorithms
- Study SRO performances
 - Comparison to standard DAQ
 - Optimize software trigger
 - Test Scalability
- Study SRO bottleneck
 - Network level
 - Node level

Reduced performance not in functionality



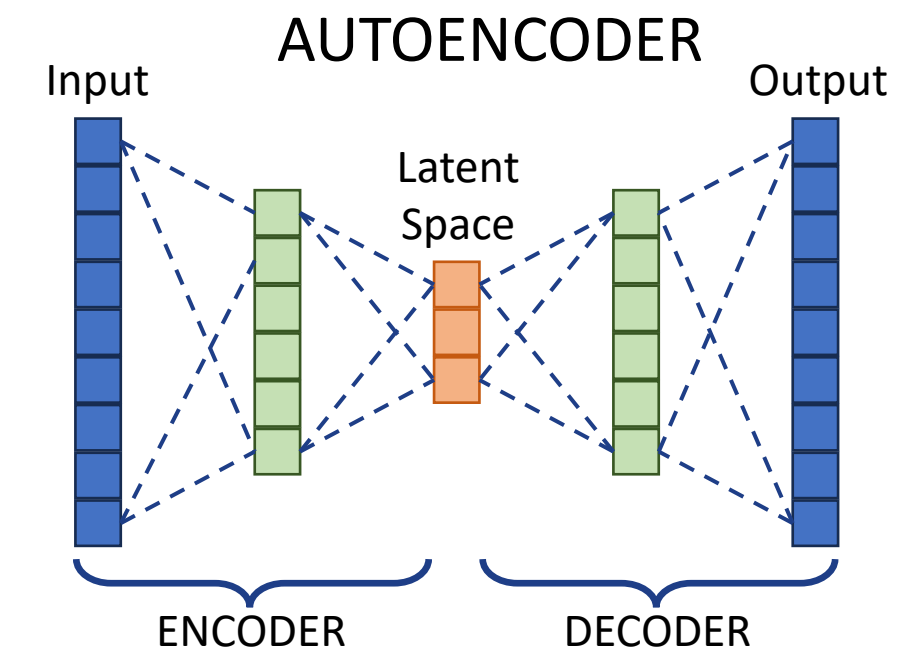
(A) Explore Single signal behavior
This tab allows the inspection of all signals at each node of the pipeline. All signal details are displayed along with the sampled waveform for immediate visual inspection.

(B) Explore Network loads
Monitor network traffic in Messages/s and kB/s at every node. Traffic across different nodes can be compared to evaluate the performance and efficiency of data compression nodes.

(C) Explore Frame router behavior
This tab displays the aggregated data after the frame router. Each frame is tagged, as are the signals originating from the two channels, highlighted in blue and yellow, respectively.

(D) Explore High level elaboration
This view displays data at the backend level. Starting from the top, it shows the raw data followed by two trigger types: the leading edge and the coincidence between the two channels.

Case study: AI Based data reduction



The Autoencoder acts as a lossy compression algorithm where error levels are manageable, allowing for a precise trade-off between compression factor and data loss. Various configurations are evaluated offline using diverse sets of real-world data.

TRAINING: Offline
INFERENCE: Online

Inference are validated through real-time acquisitions before the final implementation on high-performance servers. Future studies will focus on hardware-level integration, exploring FPGA implementation to further enhance system efficiency and performance.

Same scheme replicated on different hardware to achieve better performances

High performance Server
DELL C6400
4 x AMD EPYC 7413 24-Core Processor

HARDWARE LEVEL
ALINX VD 100
hls 4 ml

STREAM-AI
Raspberry Pi 4 Rev. B
Low-cost hardware (Educational Tool)

