An Intermediate Level Supernova Pointing Trigger for DUNE Using In-storage AI

Michael Wang (Fermilab) for the DUNE collaboration

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Deep Underground Neutrino Experiment

SURF Lead, SD

FNAL Batavia, IL

1,300 km/800 m

4 17-kton LArTPC modules

1.5 km to surface
Deep Underground Neutrino Experiment

1,300 km/800 m

1.5 km to surface

4 17-kton LArTPC modules

1 module
• 150 Anode Plane Assemblies
• 2560 wires/APA
• 384,000 channels total
• 14-bit ADC @2MHz
• > 1TB/sec !
DUNE DAQ and Trigger System

17 kton LArTPC module
150 Anode Plane Assemblies / module
2560 channels / APA

- 10 x 10Gbps links / APA
- 384,000 channels / module
- 1 FEC per 2 APAs
- Gen. TPs
- Dispatch trigger commands to available Event Builders
- Make trig decision & gen trigger commands
- NIC
- FEC
- DS
- EB
- Data Plot Orchestrator
- Module Level Trigger
- Network Switch
- Storage Buffer

To FNAL Offline Storage

High Level Filter

Data Flow

External Trigger Interface

LArTPC module 1
LArTPC module 2
LArTPC module 3
LArTPC module 4

> 1.5M channels

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DUNE DAQ and Trigger System

17 kton LArTPC module

Raw data from detector

Module

Level

Trigger

Data Flow

Orchestrator

Storage Buffer

Dispatch trigger commands to available Event Builders

make trig decision & gen trigger commands

High Level Filter

To FNAL Offline Storage

Gen. TPs

FEC

1 FEC per 2 APAs

150 Anode Plane Assemblies / module

2560 channels / APA LArTPC module 1

LArTPC module 2

LArTPC module 3

LArTPC module 4

External Trigger Interface

> 1.5M channels

DS DS DS DS

EB EB EB

Network Switch

Network Switch

NIC

NIC

NIC

IC

CPU

SSD

DAQ Front End Computer (FEC)

Raw data from detector

To DS computer & event builders

Module Level Trigger

Make trigger decision & genera trigger commands

Data Flow Orchestrator

External Trigger Interface

SSD

CPU

To DS computer & event builders

FEC

NIC

RAM

DAQ Front End Computer (FEC)

17 kton LArTPC module

Raw data from detector
DUNE SNB Trigger

- Raw data from detector
- NIC
- CPU
- NIC
- RAM
- 10 s circular buffer
- 10 sec
- DAQ Front End Computer (FEC)
- 100 sec SNB data

To DS computer & event builders

SNB trigger

Gate

#interactions

60

secs

6/4/20246

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DUNE SNB Trigger – baseline requirements

- Baseline trigger provides no pointing information, which is needed for optical follow-ups
- Idea is to send data back to FNAL for more processing
- 100 Gbps links from underground caverns to surface & back to FNAL
- Best case scenario: 120 TB/module would take ~3 hrs to transfer
- Could be worse: DUNE requirement is to copy data back within 24 h
SURFing the cosmic wave

shock breakout
(SBO)

Fe core ~1.4 M☉
SURFing the cosmic wave

shock breakout (SBO)
Shock propagation time

- Delay between arrival of neutrinos and optical light: ~shock propagation time
- Range: ~1 min to several days
- Unless progenitor is red supergiant, network transfer time back to FNAL alone already exceeds available window of opportunity

SN 1987A ~3 hrs

Computing paradigm shift

- **A solution:** Near-data computing
  - Instead of moving data to processors, move processing to the data
- **One example is Computational Storage Technology**
  - COTS products available now
Strategy for fast pointing determination

• Two step approach:
  – Data reduction: perform in situ on data, using FPGAs or GPUs to reduce buffered SNB data to a point where it can be transported quickly over conventional network to destination server
  – Pointing determination: execute optimized “offline-like” pointing analysis on the reduced data set on the server
• Use AI/ML methods for the in situ data reduction step:
  – Run ML models on accelerators like FPGAs, GPUs, etc.
  – Fast inference times for low latencies
  – Apply ML methods on both:
    • Raw 2D LArTPC wire plane images
    • Raw 1D LArTPC wire waveforms
Strategy for fast pointing determination: hardware

~75 DAQ front end computers performing near-data computing to reduce buffered SNB data

Perform pointing analysis on reduced data
Strategy for fast pointing determination: algorithms

ML-based *in situ* data reduction

Radiological Bkg rejection with 2DCNN → Raw waveform ROI finding with 1DCNN → Denoising raw waveforms in ROIs with 1D AutoEncoder

Raw wire plane data

Dataprep (sig-proc) → Gaushit → SP Solver → DisAmbig → TrajCluster → PmTrack → PointTreeRes → Likelihood fit for direction

“Offline-like” reconstruction and pointing analysis
Radiological background rejection with 2D-CNN

Wire number

Time tick

(512 ns / tick)
ROI finding with 1D-CNN and denoising with 1D-AE
ML-based data size reduction estimates

• Data rate from 1 far detector module (horizontal drift):
  – 150 APAs × 2560 ch/APA × 14 bits/sample × 2 Msamples/sec ~ 1.2 TB/s

• Buffered supernova data per detector module:
  – 100 seconds: 120 TB
  – For pointing determination, focus on first 10 seconds: 12 TB

• Estimated size of data per SN neutrino candidate from ML-based reduction pipeline:
  – CC: 47,306 bytes
  – ES: 29,680 bytes

• Assuming 2DCNN rejects 100% radiologicals, assume we retain all CC + ES neutrinos interactions:
  – 3,300 CC × 47,306 bytes + 326 ES × 29,680 bytes ~ 158 MB for all 4 modules
  – 48 TB → 0.000151 TB ~ over 5 orders of magnitude reduction!
Execution time for track reconstruction on reduced sample

- Track reconstruction pipeline:

  ![Track reconstruction pipeline diagram]

- Use of 1D denoising AutoEncoder to clean up electronics noise of raw waveforms in ROIs from 1DCNN allows us to use “legacy” 1D FFT deconvolution in the “Dataprep” stage to speed up things.

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Reco time (sec/event)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC</td>
<td>0.061</td>
</tr>
<tr>
<td>ES</td>
<td>0.026</td>
</tr>
</tbody>
</table>

- Assume we reject all radiologicals with 2DCNN and retain all CC+ES events:
  - \(3300 \times 0.061 + 326 \times 0.026 \approx 210\) seconds = 3.5 min
  - for full DUNE detector executed using one CPU core!
Compare with no reduction case

- How long would it take to process the SN data using the reco pipeline in the previous slide on a full 10 second raw dataset
- It takes ~9.5 seconds to process 1 APA worth of data in a 6000 time tick (500 ns/tick) readout window using one CPU core:
  - Assuming we dedicated one CPU core to 1 APA on each DAQ readout computer:
    - 100 seconds of SN data would take 88 hrs to complete
    - 1st 10 seconds of SN data would take ~9 hrs to complete
- For simplicity assume all 4 detector modules identical to first horizontal drift module, i.e. 150 APAs per module:
  - 9 hrs using $4 \times 150 = 600$ CPU cores versus 3.5 min using 1 CPU core!
Execution time for ML-based data reduction pipeline

• ML-based data reduction algorithm is meant to run on FPGAs that access buffered SN data on SSDs directly. FPGA’s main advantage over GPU is lower power consumption – important because of limited power budget in SURF underground caverns.

• However, since we were not able to get results in time, we benchmarked the algorithm on a typical GPU to get an idea of what is achievable

• Using half of an Nvidia A100 GPU*:
  – Since each front end DAQ computer serves 2 APAs
  – 15 minutes to perform the ML-based data reduction for 1 APA

* A100 is a datacenter GPU and not the ideal for this application due to power consumption. Only used here to get an idea of inference times possible. There are other GPUs targeted at low latency inference combined with low power consumption

• Total of ~20 minutes to do ML-based data reduction + track reconstruction
  – Still considerably less time than it takes just to transfer the SN data back to Fermilab:
    • 10 seconds of SN data for all 4 modules: 48 TB takes ~1 hr to transfer over 100 Gbps ethernet
In-storage ML-based data reduction

- Host CPU
- RAM
- PCIe
- FPGA
- NVMe SSD
- mem

Supernova readout buffer: PCIe Gen4 NVMe SSD modules on PCIe carrier

Prototype DUNE DAQ front end computer

Xilinx FPGA card

Fermilab

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Hardware implementation 1

Full-size frames sent to 2dcnn for inference

<table>
<thead>
<tr>
<th>Plane</th>
<th>Input frame size</th>
</tr>
</thead>
<tbody>
<tr>
<td>induction</td>
<td>200 x 1,148(9)</td>
</tr>
<tr>
<td>collection</td>
<td>200 x 480</td>
</tr>
</tbody>
</table>

Inference time/frame ~3.2 ms
Compared with ~0.5 ms for the GPU

Plane Input frame size

induction 200 x 1,148 (9)

collection 200 x 480
Hardware implementation 2

- Looks promising, achieving inference times of $O(10)$ us with input frame widths of 64
- More compact: more instances can be implemented for parallel execution
- Requires more testing with wider input frames and inclusion of all pre-processing steps
Signal efficiencies when using ML-based data reduction

- Fast execution times are useless unless we retain a significant amount of the SN neutrino interactions. Here we compare signal efficiencies after the GausHit finder stage between a standard full dataset reconstruction and our ML-based reduced dataset reconstruction:

<table>
<thead>
<tr>
<th>Reconstruction chain</th>
<th>Sig eff for primary trk hits</th>
<th>Sig eff for daughter trk hits</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>U</td>
<td>V</td>
</tr>
<tr>
<td>ML-reduced (1D deconvolution)</td>
<td>0.69</td>
<td>0.71</td>
</tr>
<tr>
<td>Standard full dataset (2D deconvolution)</td>
<td>0.68</td>
<td>0.67</td>
</tr>
</tbody>
</table>

GausHit finder hit efficiencies for fully simulated nuES events

- Able to achieve same signal efficiencies but with tremendous reduction in execution time!
Energy distributions

- Here we compare the reconstructed energy of the scattered electron in the SN ES interactions between the standard full-dataset reconstruction and the ML-based reduced dataset reconstruction:

- Basically, the ML-based reconstruction pipeline produces identical results as a standard offline reconstruction.
More info on DUNE SN pointing capability & ML models used

- For more details on DUNE’s supernova pointing capabilities, please refer to:
  - Updated version to be published:

- For more details on ML models used in this work:
  - Clair, J. Real-Time Detection of Low-Energy Events for the DUNE Data Selection System. DUNE-doc-27333-v1. (2DCNN)
Conclusions

• Common assumption: DUNE SN processing requires significant computing resources: processing, network, and storage
  – SN data needs to be transferred back to FNAL for more processing to determine direction
  – HPC sites were also being considered for this purpose

• What we have demonstrated: applying ML-based data reduction as early as possible can reduce data to such a degree that makes it possible to perform offline-like analysis on-site with minimal computing resources – i.e. on a single server:
  – total processing times less than network transfer time back to FNAL appear achievable
  – no loss in quality of results wrt full reconstruction/analysis

• This has positive implications for previous assumptions about DUNE’s computing requirements, perhaps warranting a re-examination of these assumptions
Conclusions (continued)

• While results look promising, this is a work in progress, and more work needs to be done:
  – Single largest contribution to the total processing time is the 2DCNN-based radiological background rejection:
    • Focusing on reducing 2DCNN inference time will reap the largest benefits
  – Continue exploring hardware accelerator options:
    • Continue with FPGA implementation and optimization
    • Benchmark GPUs geared towards low-latency inference applications & low power
    • Explore dedicated AI inference chips
  – Include algorithms for discriminating ES vs CC and optimize these algorithms
  – Implement end-to-end demonstrator within dune-daq framework
People directly involved in this effort

- **Fermilab**
  - Maira Khan, Jovan Mitrevski, Ben Hawks, Tom Junk, Tingjun Yang, Jennifer Ngadiuba, Mike Wang, Pengfei Ding (now at LBNL)

- **Duke University**
  - Kate Scholberg, Janina Hakenmueller, Van Tha Bik Lian

- **Columbia University**
  - Georgia Karagiorgi, Judicael Claire, Guanqun Ge, Akshay Malige

- **York University**
  - Tejin Cai (now at Synopsys Inc.)

- **Iowa State University**
  - Amanda Weinstein, Avik Ghosh
Thank you!
How a LArTPC works