

Summary of Computing+Machine Learning Parallel Session

CPAD 2018

T. Wongjirad (Tufts)

on behalf of the session conveners

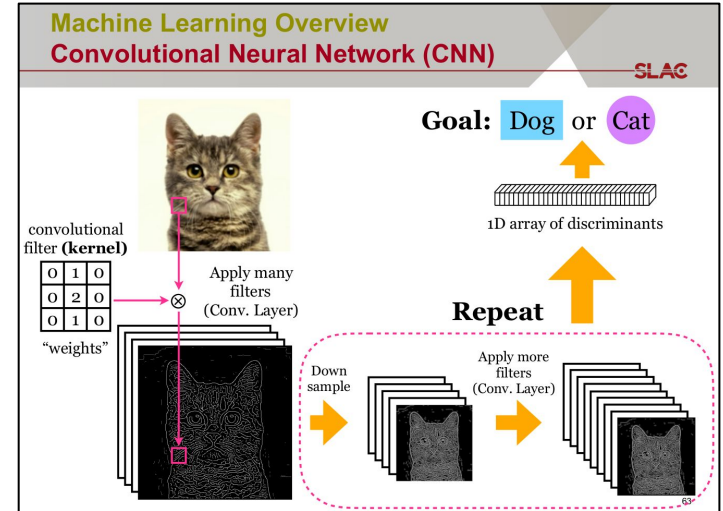
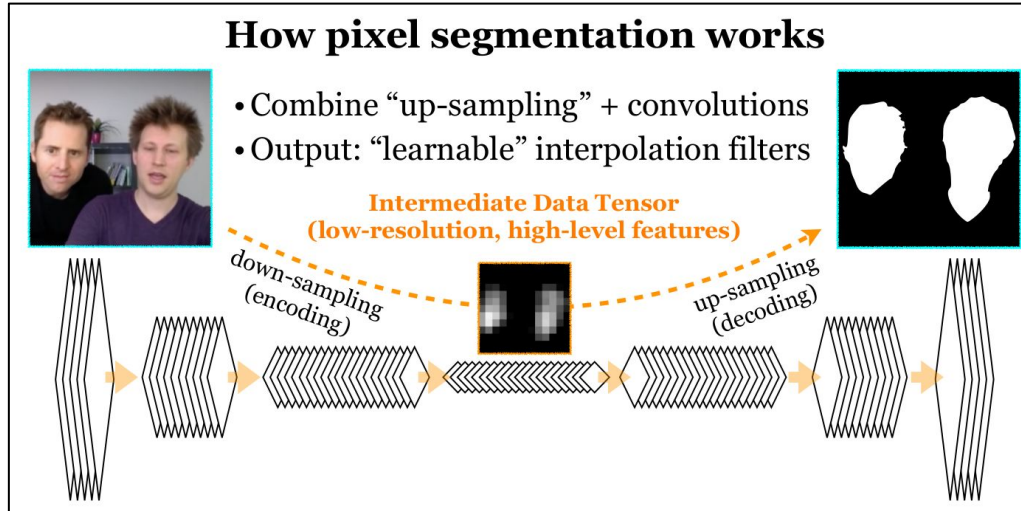
S. Gleyzer, O. Gutsche

Computing & Machine Learning

- Three parallel sessions
- 12 Talks (+1 plenary session)
- Many thanks to all of the speakers for presenting an exciting diverse set of talks
- And thanks to the audience for questions and discussions
- Due to time -- please forgive me if I missed names and slide links

Adoption of Deep Neural Networks

- Some quick descriptions of these algorithms (backups have more details) can be found in K. Terao's talk
- <https://indico.fnal.gov/event/18104/session/23/contribution/77>



Deep Neural Networks

- Deep neural networks featured in majority of talks
- Such algorithms, e.g. convolutional neural networks, have enabled advances in fields such as computer vision -- bringing techniques to particle physics

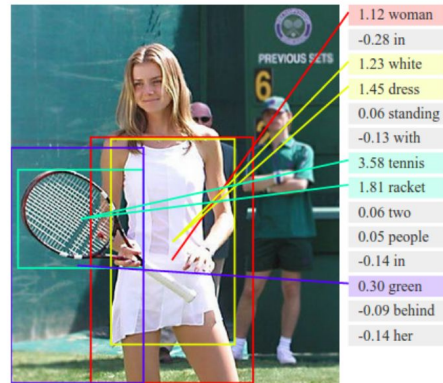
Object detection and instance segmentation



Caption generation/scene parsing



"girl in pink dress is jumping in air."

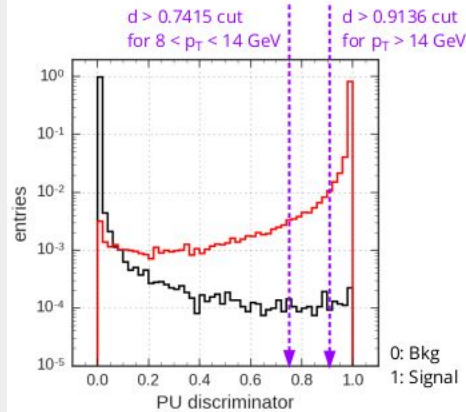


Themes

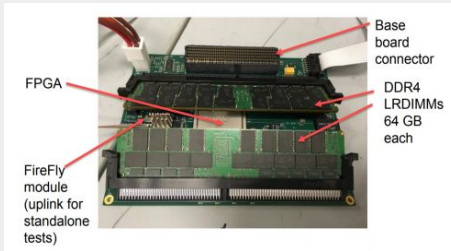
- Algorithm development in a variety of contexts
 - LHC: Jet ID, track recon.
 - Liquid argon neutrino experiments
 - Cherenkov/scintillator neutrino experiments
 - Adoption of machine learning techniques
- Deployment of algorithms beyond CPUs
 - Deploying Machine Learning Networks on FPGAs
 - Track reconstruction using quantum annealers
- Bringing Everything Together
 - Deploying into online systems
 - Organizing training in computing, ML, etc. in order to maintain the rapid pace of development of new tools

LHC Applications

- Particle ID: quark/gluon, electron/photon, and more.
- L1 muon reconstruction using NN on FPGAs



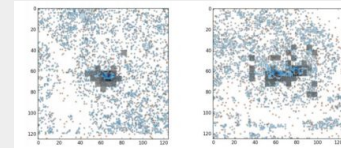
Jia Fu Low et al.
(Monday afternoon)



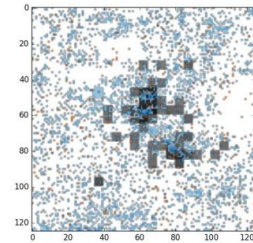
- From simulation studies, we have achieved roughly 4x rate reduction with the addition of the new muon detectors. The overall efficiency has also been improved.
 - Still work in progress.

<https://indico.fnal.gov/event/18104/session/23/contribution/71/material/0/0.pdf>

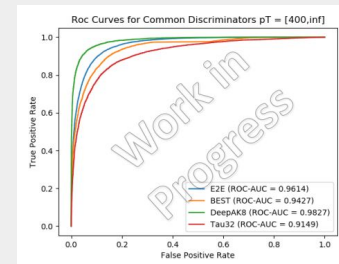
B. Burkle et al. (Tues morning)



Jet images coming from QCD sample



Jet images coming from Top decay



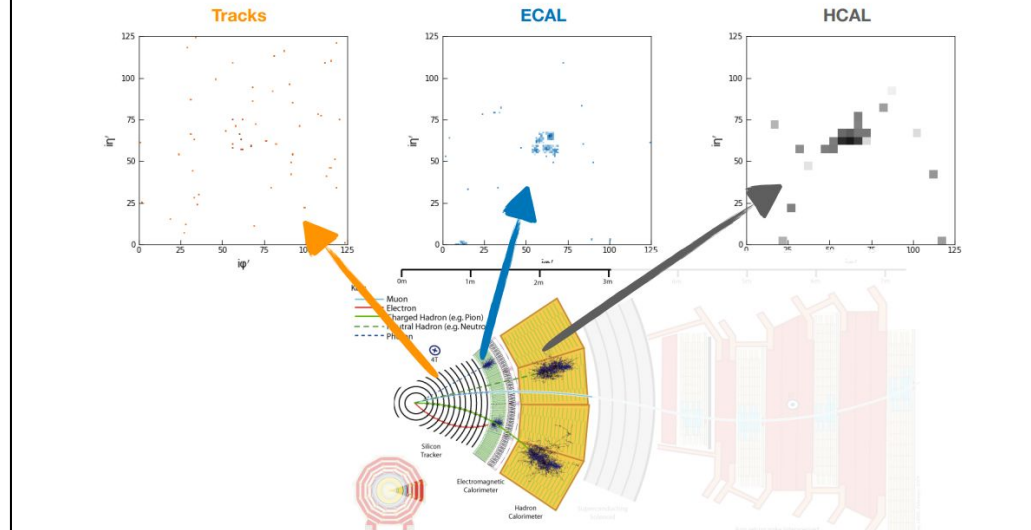
<https://indico.fnal.gov/event/18104/session/23/contribution/147/material/0/0.pdf>

Example: End2End method

Simultaneously provide images of energy depositions from several subsystems to convolutional neural networks

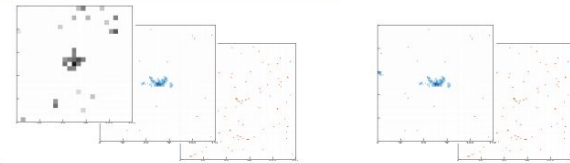
E Usai et al (Monday afternoon)

Detector images



Example: quark vs. gluon jet

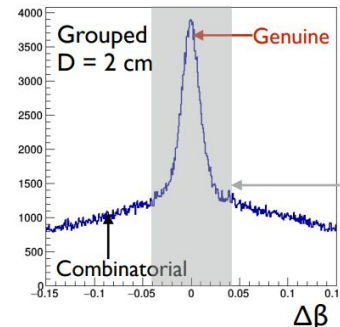
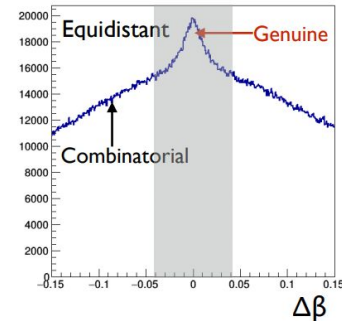
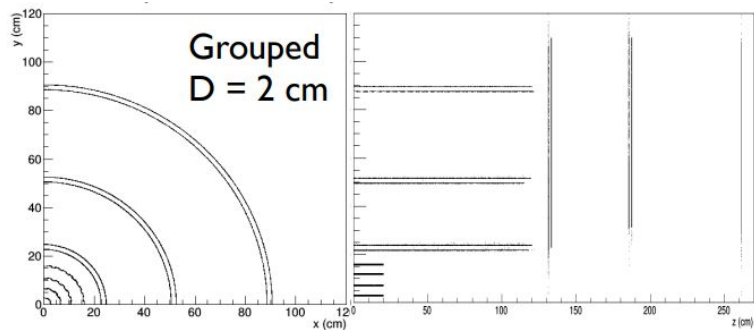
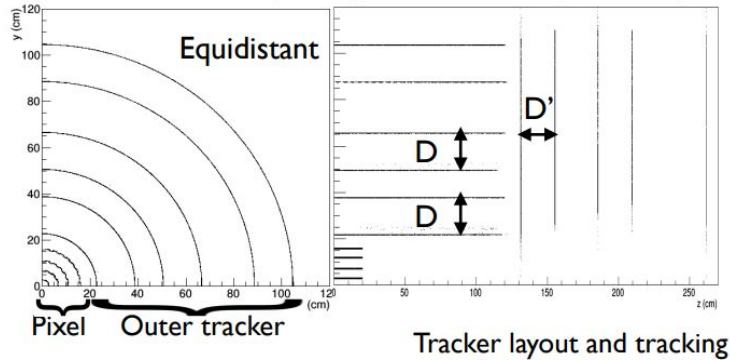
Subsystems combined



	ROC AUC
E2E image, ECAL+HCAL+Tracks	0.8077 ± 0.0003*
RecNN, ascending-p_T	0.8017 ± 0.0003*
RecNN, descending-p_T	0.802
RecNN, anti-k_T	0.801
RecNN, Cambridge/Aachen	0.801
RecNN, no rotation/reclustering	0.800
RecNN, k_T	0.800
RecNN, k_T-collinear10-max	0.799
RecNN, random	0.797

LHC Applications -- Not all machine learning

- Studying the impact of the tracker detector layout on CPU usage on reconstruction time and software



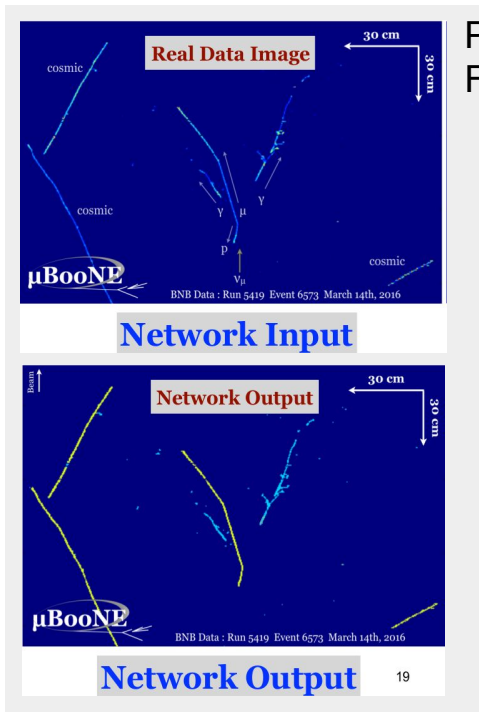
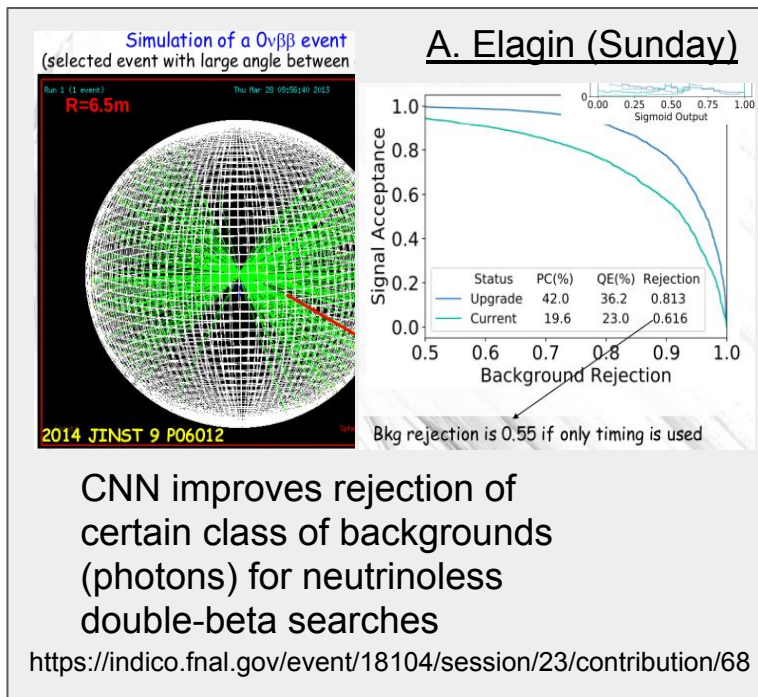
V. KRUTELYOV et al.
(Monday)

One example:
false tracks reduced

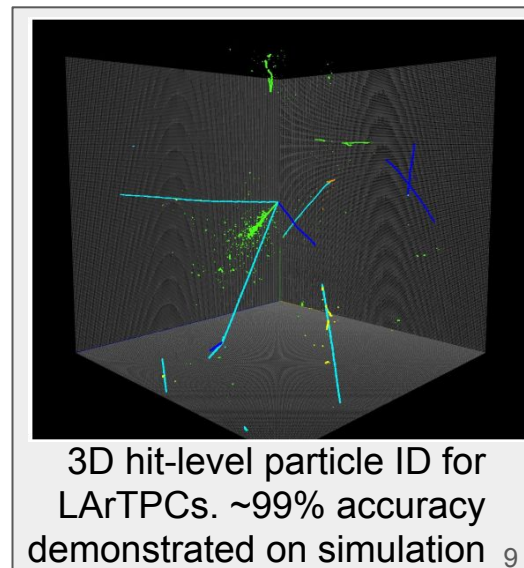
Translates to
reduced CPU wall
time

Neutrino Experiments

- Heard from applications to liquid argon TPCs (GeV events) to Cherenkov/Scintillator detectors (MeV events)

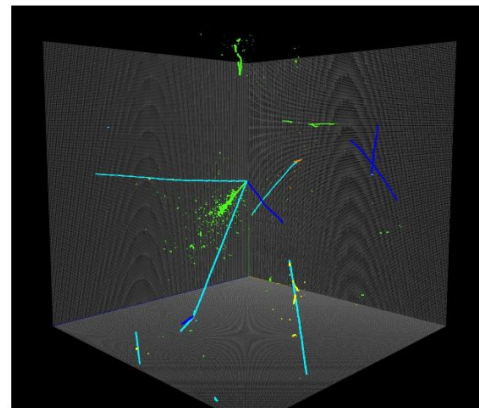


Pixel-level particle ID (on data)
For LArTPC images (uBooNE)



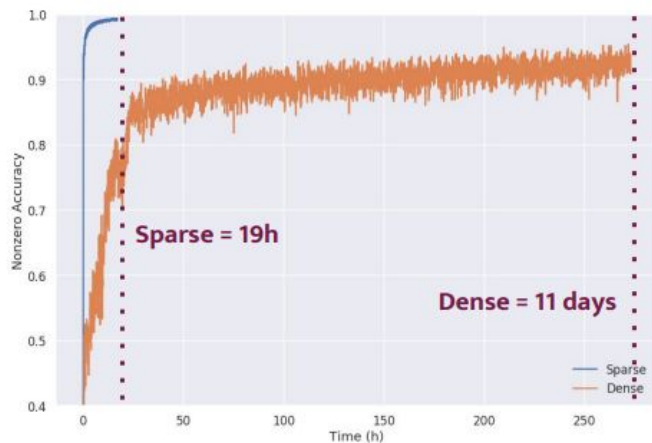
Sparse Operations

- CNN operation on 3D space-points enabled by **using sparse matrix operations rather than dense operations** -- much better fit to liquid argon TPC data (and particle physics data)



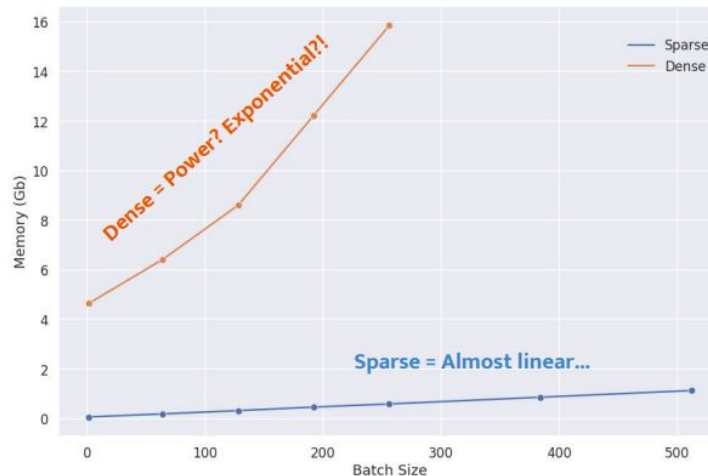
L. Domine et al (Tues Morning)

Training speed up



Nonzero Accuracy (training) vs Wall Time

Much less memory usage

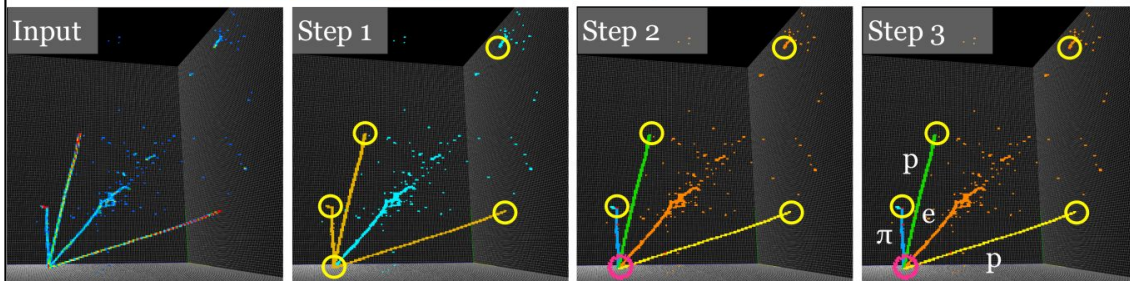


Online/Offline deployment of full reco. chain

- Such technical developments allow for fast training AND more efficient deployment/inference
- Allow us to reach eventual, ever-growing ambitions

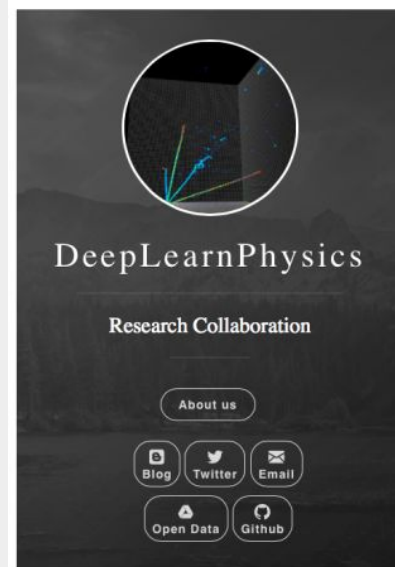
Where we are...

- 1. Space point (track edges) + pixel feature annotation
- 2. Vertex finding + particle clustering
- 3. Particle type + energy/momentum
- 4. Hierarchy building



Aiming to **complete the full chain v.1** in early 2019, move to **physics analysis applications**

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Code, tutorials, data sets
<http://deeplearnphysics.org/>

K. Terao et al.
Sunday

11

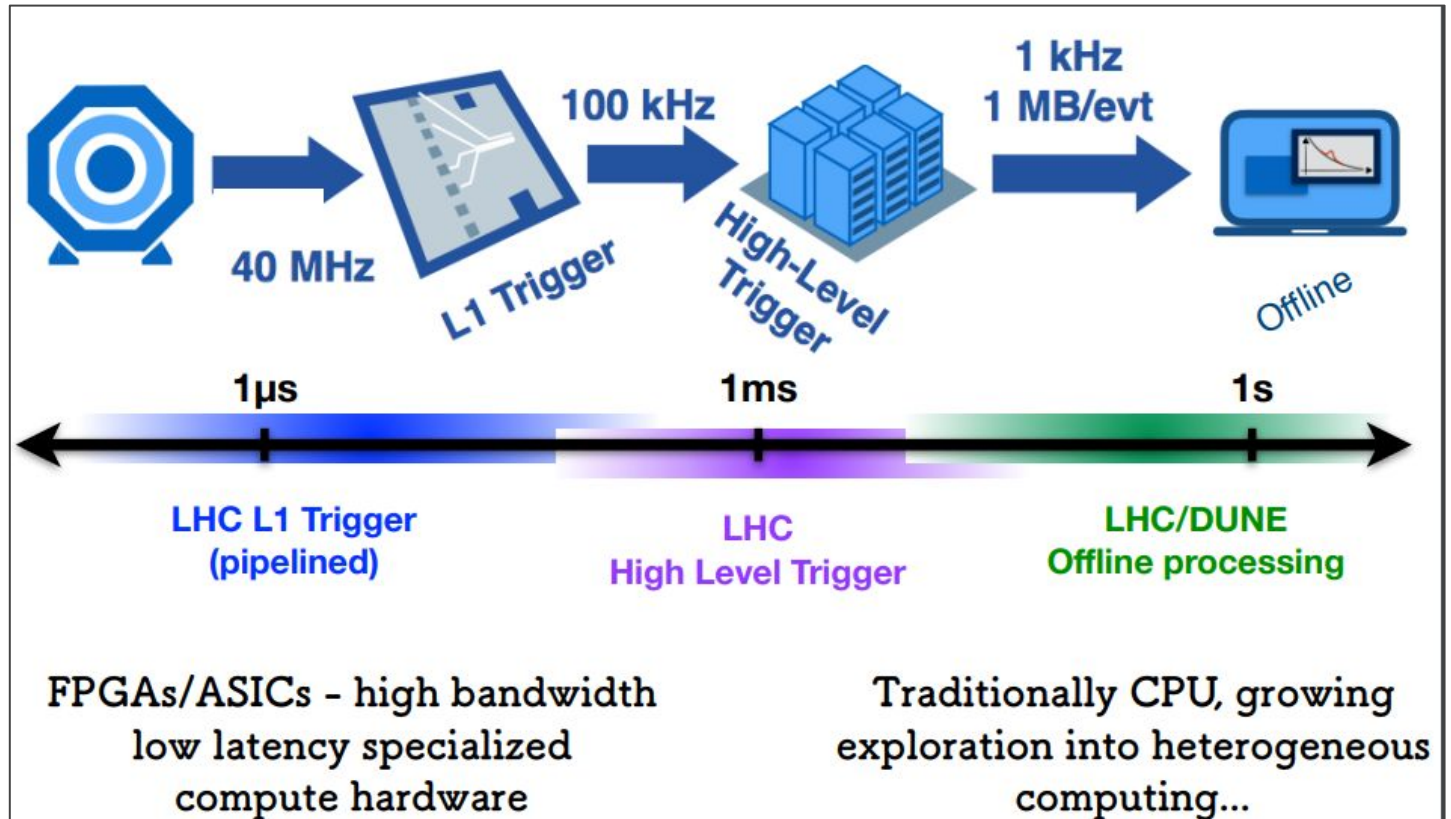
Online/Offline deployment of reco. chain

M. Liu
Mon Plenary

These algorithms most efficient on specialized devices -- which are not always as readily available as CPU cluster

(surge in field enabled by GPUs developed to run increasingly demanding video games)

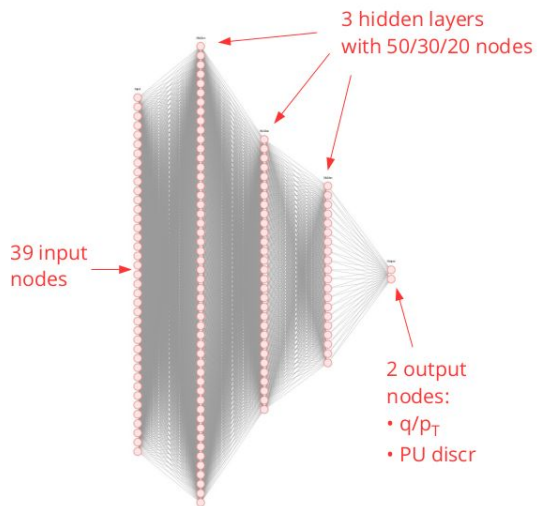
Solving same problems as industry -- opportunities for co-development



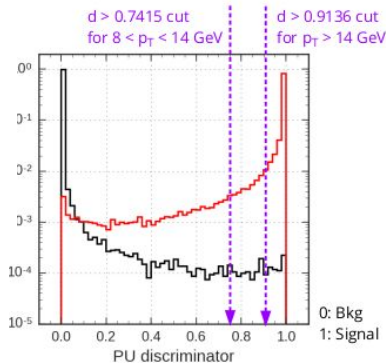
<https://indico.fnal.gov/event/18104/session/8/contribution/16/material/0/0.pdf>

Deployment of NN for L1 Muon Selection on FPGAs

- From simulation studies, we have achieved roughly 4x rate reduction with the addition of the new muon detectors. The overall efficiency has also been improved.
 - Still work in progress.



Jia Fu Low et al. (Monday afternoon)



- NN understudy deployed using HLS2ML -- exciting tool to ease the deployment of networks on FPGAs



D. Rankin et al (Monday afternoon)

<https://indico.fnal.gov/event/18104/session/23/contribution/73>

Problems for all next-gen experiments: EIC

Analyze larger, more complex datasets a challenge for everyone

Talk from Electron Ion Collider tackling realtime processing (and beyond)

M. DIEFENTHALER et al.
(Monday afternoon)

Streaming Readout III: Prototype DAQ systems being discussed

BDX dark matter experiment at JLAB

- digitization: INFN “wave board” digitizer (250 MHz, 14 bit, 12 ch)
- online event reconstruction: TRIDAS system from KM3NeT
- ongoing data validation of prototype syste,

CBM upcoming fixed-target heavy-ion experiment at FAIR

- event rates up to 10MHz (current heavy-ion experiments 100Hz – several kHz)
- no hardware trigger, real-time data selection exclusively on CPU (under development)
- validation with detector prototypes (eTOF@STAR) and with full-system tests (mCBM@GSI)

JLAB streaming readout for upcoming TDIS, SoLid, and EIC experiments

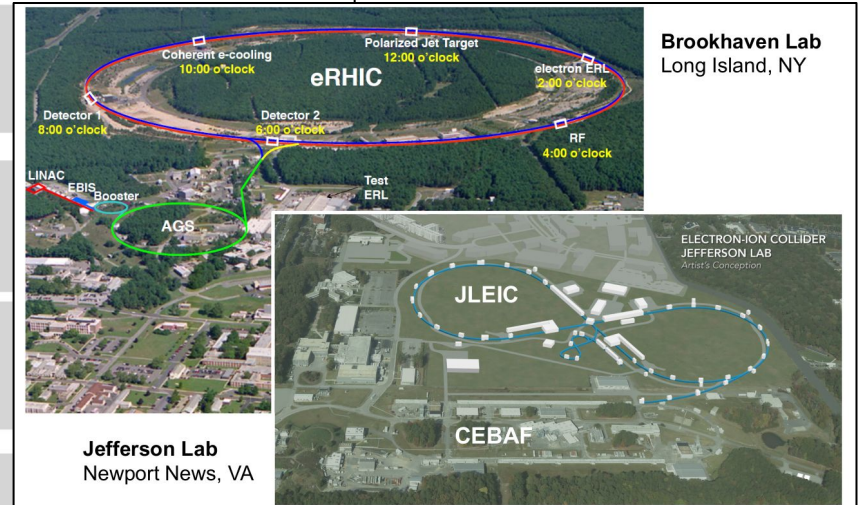
- build various generic streaming DAQ using existing hardware at JLAB
- could serve as an upgrade of existing DAQ systems at JLAB
- gain valuable experience for R&D for future hardware

PHENIX heavy-ion experiment and upgrades at BNL

- 15kHz signal collisions, 1.4M channels streaming

sPHENIX upgrade of PHENIX experiment

- sPHENIX TPC: 160k channels 10b flash ADC @ 20MHz with SAMPA ASIC -> 2 Tbit/s stream rate.
- BNL-712/FELIX-type DAQ with data rate of 200 Gbit/s



Glimpse of the future

- Demonstration of track reconstruction using a quantum annealer
- Exciting step in quantum computing

L. Linder et al. (Sunday afternoon)

Map the problem of selecting true trajectory components from set of possible to the minimization of energy of a quantum system

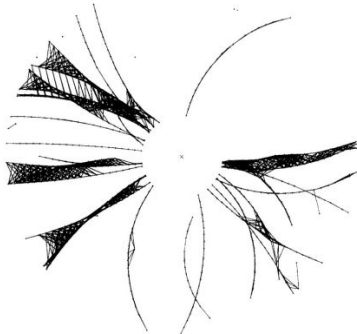


Fig. 1. Display of all generated lines for a real $Z^0 \rightarrow$ hadrons (XY projection).

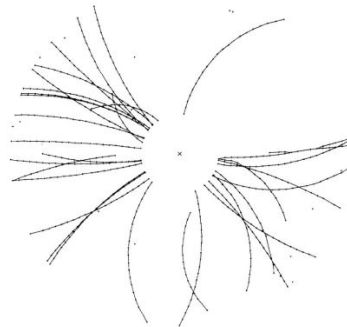


Fig. 3. Display of the activated lines after convergence for a real $Z^0 \rightarrow$ hadrons (XY projection).

source: [fast track finding with neural nets](#)



quantum machine instruction (QMI)
objective function:

$$O(a; b; q) = \sum_{i=1}^N a_i q_i + \sum_i^N \sum_j^N b_{ij} q_i q_j \quad q_i \in \{0, 1\}$$

QUBO

Quadratic Unconstrained
Binary Optimisation

1. generate the set potential doublets (apply early cuts)
2. *binary classification task* to determine which doublets should be kept in the solution

<https://indico.fnal.gov/event/18104/session/23/contribution/61>

Track reco. w/ quantum annealer

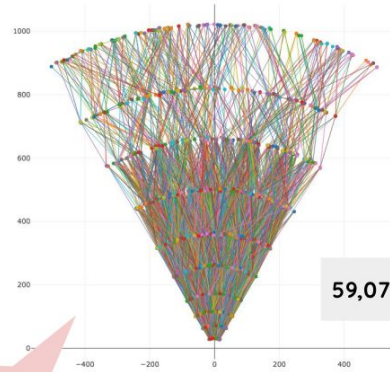
L. Linder et al. (Sunday afternoon)



Performances at low Pt

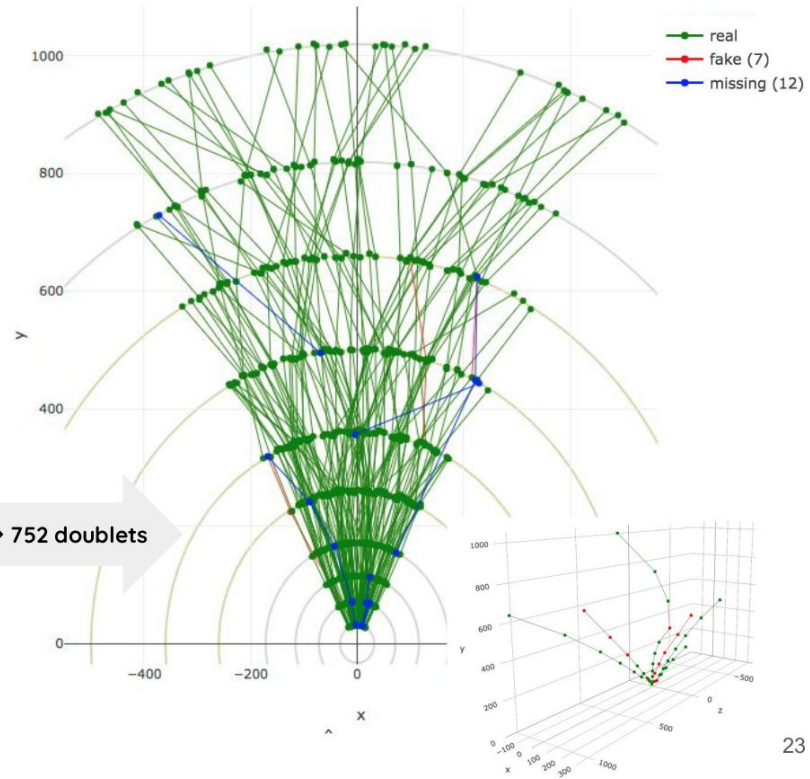
186 particles in a phi slice of $\pi/3$

precision (%): 98.5, recall (%): 98.4,
trackml score (%): **98.35**



QUBO size
68,043

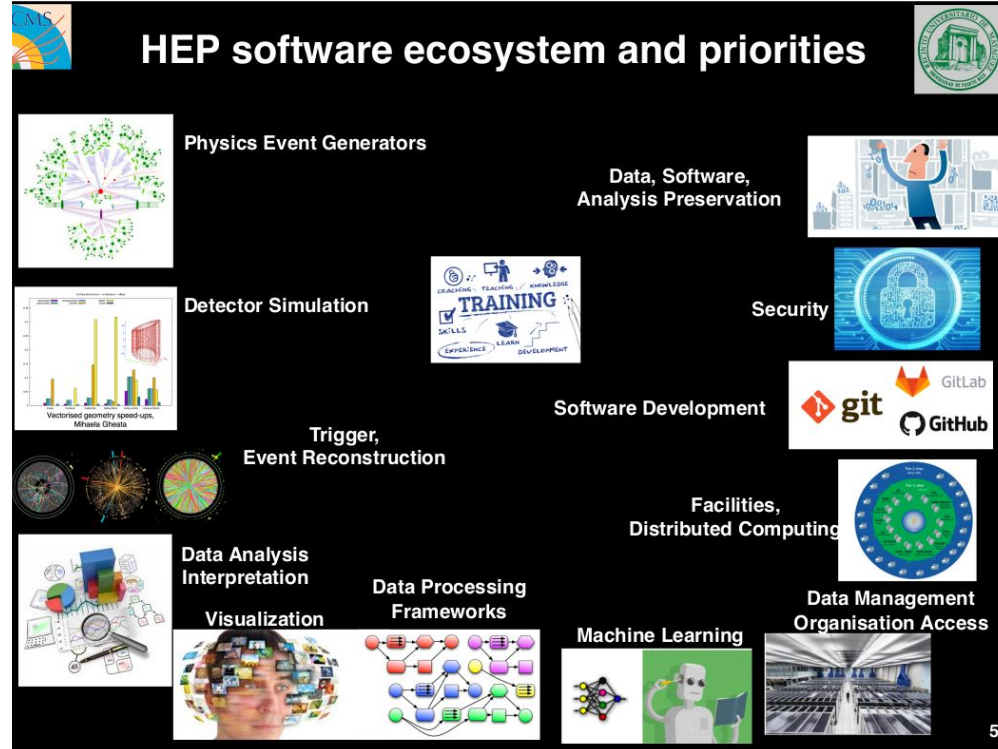
59,077 \Rightarrow 752 doublets



Training *in vivo* networks

- Accelerating R&D requires training all those are interested in joining in (not just software, detector development as well)
- Often overlooked, but critical
- Organize (often redundant) materials from different experiments for common techniques - disseminate widely, host workshops
- For ML:
 - Produce more users and developers
 - *Spur community critiques as well*

S. Malik et al. (Tues morning)



Get involved!

- ▶ IRIS-HEP website <http://iris-hep.org/>
 - ▶ Jobs on IRIS-HEP and Collaborating Projects <http://iris-hep.org/jobs>
 - ▶ General public announcement mailing list for IRIS-HEP events, talks, meetings, workshops, opportunities for training and job opportunities (subscribe to) announcements@iris-hep.org
- ▶ HSF (HEP Software foundation) - <https://hepsoftwarefoundation.org>
 - ▶ General Information about HSF (subscribe to): hsf-forum@googlegroups.com
 - ▶ Discussions and activities in the HEP Software Foundation mailing lists can be found here (General and Dedicated Forums): <https://hepsoftwarefoundation.org/forums.html>
 - ▶ You can contribute <https://hepsoftwarefoundation.org/cwp/cwp-working-groups.html>
 - ▶ HSF Events/Workshops - <https://hepsoftwarefoundation.org/events.html>
- ▶ FIRST-HEP website <http://first-hep.org>
 - ▶ Funding for participants and lecturer support for Training

Summary

- A great collection of new, promising developments
 - Theme across domains: often can (should?) employ information closer to the raw data of our detectors -- make use of the increasingly precise information coming from new detectors
 - (can provide means to preliminary performance estimates to inform hardware design as well)
- Many directions to explore -- way more than people to work on them
 - Please join!
- Clear that communities should continue to be in close communication to share advances
 - Shared code
 - Open datasets