## CLAS12 DC Tracking with Machine Learning

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### Machine Learning for CLAS12: Motivation

Largest CPU resource driver for event reconstruction is charged particle tracking

- DC Pattern recognition ~ 2 % CPU usage
- DC hit-based tracking ~ 58% CPU usage
- DC time-based tracking ~ 37% CPU usage

Targeted Areas of Improvement for CLAS12 DC Tracking:

- Processing speed
- More efficient noise rejection
- Combinatorics (ghost tracks)





### **Al Project Team**



G. Gavalian (lead) – Neural Network evaluation software integration into CLAS12 software infrastructure.

V. Ziegler – AI-Assisted tracking code implementation. Benchmarking, testing and debugging of tracking code.



Center For Real-Time Computing (CRTC): N. Chrisochoides, P. Thomadakis, A. Angelopoulos – NN training and interface to CLAS12 framework; computing resources for the project (GPU farm equipped with high-end NVIDIA V100 GPUs).

- > Testing different NN to determine which one is most suitable for CLAS12
- Writing of software package using Tensorflow/Keras/SciLearn to train drift chamber data, and run inference.
- Development of Python interface for reading HIPO data and writing inference results into Output.



### **Aims and Approach**

- Al project phase 1 goals:
  - Use AI to identify which DC track segments are consistent with being *on-track*.
  - Save these data in a dedicated bank that is used by the tracking code as input, by-passing traditional pattern recognition phase, and hit-based tracking combinatorial selection algorithms.

- Approach:
  - Provide samples consisting of hits belonging to track segments to the neural network: training samples and testing samples.



### **Choosing an AI Network**





### **Boosted Decision Trees**

- Takes a set of input features and divides data recursively based on those features.
  - -Nodes: split data based on value of input features.
  - -Leaves: terminal nodes; gives outcome probability.
- Tree Boosting combines trees into a classifier.





### **Multi-Layer Perceptron**

- Collection of connected units or nodes (artificial neurons) that transmit information from one layer to the next.
  - Signal at node: real number.
  - Output of each neuron: function of sum of inputs.
  - Edges: connections carrying a weight that adjusts the learning process.
- Multiple hidden layers. Utilizes supervised learning (back-propagation for training).





### **Convolutional Neural Network**

- Category of deep Neural Networks commonly used to analyze images.
- Input and output layers with multiple hidden layers.
  - *Convolutional* layers that convolve the input and pass it to the next layer.
  - Includes *pooling* layers that streamline the underlying computation.
  - Fully *connected* layers connecting every neuron in one layer to every neuron in another layer.





### **Neural Network Samples Used for Training**

- 3 samples with different input parameters tested for training
  - -BDT & MLP inputs [sample 6]
    - Average wire number of superlayer 1 segment → mapped to a local point
    - Angle between segment local points in superlayer 1 & 2
    - Average wire number of superlayer 3 segment → mapped to a local point
    - Angle between segment local points in superlayer 3 & 4
    - Average wire number of superlayer 5 segment → mapped to a local point
    - Angle between segment local points in superlayer 5 & 6
  - -MLP inputs [sample 36]
    - Array of 36 numbers with wire (H.O.T.) number (or average wire number for double hit) for each of the 36 DC layers.
  - CNN inputs [sample 4032]
    - Picture with 36 x 112 dimensions passed to the network: if wire (H.O.T.) active → white pixel, else, black pixel.



# Illustration of Selected Segments from the MLP after Training





### **Al Performance Accuracy Categorization**

- NN returns a probability (softmax fcn in last layer of classifier) for track candidates.
- Based on this probability a label is created (1: true, 0: false) to flag candidates.
- Categorization of NN outcome based on correct estimation of the track candidate:
  - -A1: # samples with correctly identified tracks / # input samples; no mis-identified tracks.
    - Only one track identified in given group of hits. This track candidate is the correct one.
  - Ac: # samples with correctly identified track + mis-id<sup>ed</sup> candidates/ # input samples; i.e. contains False Positives.
    - Multiple candidates identified. Contains candidates with highest probability that do not correspond to correct tracks (*False Positives*).
  - Ah: # samples with correctly identified tracks / # input samples; with the valid track assigned the highest probability.
    - Multiple candidates identified. Candidates with highest probability that are correctly identified.
  - -Af: # samples with correct track not-identified / # input samples; i.e. False Negatives



### **Accuracy Scores for Al Networks Tested**

- Preliminary results obtained with training samples split into multiple sets
  - Split data using DC data corresponding to a 50 nA sample (Run 5038)
    - Using sectors, 1, 3, 4, 5, 6 for training;
    - Using sector 2 for testing.
- Best track finding accuracy with CNN and MLP.
- More tests being done.

Method/Train set	Split ¢	Test Set/Format <sup>≑</sup>	A1 ÷	Ac ÷	Ah ¢	Af ÷	Training Acc +	Validation Acc +	Time to train (sec) +	Time to predict (sec)
CNN/10-7-19	10/90	10-7-19/4032	0.915	0.511	0.832	0.084	0.9389	0.900	199	0.0012
	20/80	10-7-19/4032	0.935	0.450	0.863	0.064	0.9310	0.9136	226.1	0.0012
	30/70	10-7-19/4032	0.945	0.389	0.878	0.054	0.934	0.924	257.1	0.0012
	40/60	10-7-19/4032	0.955	0.382	0.885	0.044	0.934	0.926	288.1	0.001
	50/50	10-7-19/4032	0.944	0.331	0.880	0.055	0.934	0.931	319	0.001
	60/40	10-7-19/4032	0.954	0.353	0.888	0.045	0.934	0.93	347.4	0.0013
	70/30	10-7-19/4032	0.954	0.350	0.885	0.045	0.9343	0.9325	380.8	0.0014
	80/20	10-7-19/4032	0.959	0.327	0.892	0.040	0.9344	0.9315	412.4	0.0014
	90/10	10-7-19/4032	0.956	0.332	0.880	0.043	0.9347	0.9332	444.3	0.0014
	100/0	10-7-19/4032	0.964	0.301	0.894	0.035	0.934	N/A	457	0.0012
ExtraTrees/10- 7-19	10/90	10-7-19/6	0.923	0.241	0.914	0.077	1.0	0.92	0.2	0.000005
	20/80	10-7-19/6	0.921	0.217	0.914	0.078	1.0	0.924	0.3	0.000005
	30/70	10-7-19/6	0.923	0.217	0.912	0.076	1.0	0.925	0.4	0.000005
	40/60	10-7-19/6	0.927	0.205	0.914	0.072	1.0	0.927	0.6	0.000005
	50/50	10-7-19/6	0.930	0.204	0.916	0.069	1.0	0.928	0.7	0.000005
	60/40	10-7-19/6	0.929	0.206	0.918	0.070	1.0	0.915	0.8	0.000005
	70/30	10-7-19/6	0.932	0.203	0.92	0.067	1.0	0.93	1.0	0.000005
	80/20	10-7-19/6	0.933	0.199	0.918	0.066	1.0	0.917	1.2	0.000005
	90/10	10-7-19/6	0.933	0.197	0.919	0.066	0.9999	0.931	1.3	0.000005
	100/0	10-7-19/6	0.933	0.199	0.919	0.066	0.9999	N/A	1.7	0.000005
	100/0	10-7-19/36	0.910	0.339	0.883	0.089	0.9999	N/A	8.4	0.000005
MI B/10-7-10	100/0	10-7-19/6	0.965	0.202	0.921	0.034	0.947	N/A	252 (CPU)	0.000004
WILF/10-7-19	100/0	10-7-19/36	0.920	0.312	0.849	0.079	0.921	N/A	546 (CPU)	0.00001



### **Accuracy Scores for Al Networks Tested**

NN	A1	Ac	Ah	Af	Training Accuracy	Training Time	Prediction Time
CNN	0.964	0.301	0.894	0.035	93.4%	457 sec	0.0012 sec
BDT	0.933	0.199	0.919	0.066	99.9%	1.7 s	0.000005 sec
MLP	0.965	0.202	0.921	0.034	94.7%	252 (CPU)	0.000004 sec

A1: # samples with correctly identified tracks / # input samples; no mis-identified tracks.

Ac: # samples with correctly identified track + mis-id<sup>ed</sup> candidates/ # input samples; i.e. contains *False Positives*.

Ah: # samples with correctly identified tracks / # input samples; with the valid track assigned the highest probability.

Af: # samples with correct track not-identified / # input samples;

i.e. False Negatives



### **Implementation in Current Tracking**



### **Expected Performance Improvement**

- Hits-On-Track saved in NN Bank.
- Developed the API to use new bank for seeding in DC package.
- Dedicated service to run AI reconstruction if the NN hits bank exists in the HIPO file.
- Python interface to HIPO being developed to put the results of the NN into a HIPO file.





• Even with unoptimized NN efficiency, the gain in reconstruction speed will lead substantial time gains in (re-) calibration of data.



### **Current Status & Summary**

- DC Tracking modified to work with Neural-Network-predicted Hits-On-Track. (Done)
- Framework in python to train and test track candidates (done)
- Implementation of Neural Network software into workflow (in progress):
  - -Interface to HIPO with python to read track candidates.
  - Interface with TensorFlow to get track candidate predictions and write them into the HIPO file.

- TO-DO
  - Pre-requisite for testing performance in reconstruction (efficiency, accuracy, speed).
  - Training on HIPO 4 data (varying conditions).
  - -Validation of accuracy using data and MC samples (i.e. sample with background-merging).
  - -Possibly include the prediction algorithm into decoding.
  - Dedicated clustering service (ongoing).



### **BACK-UP SLIDES**



### **Network Configuration**

- ◆ Basic VGG16 model was used to train on track reconstruction images.
- ✦ Initial sample of event 20K for positive and negative samples.
- ✦ Inference time ~3ms (GPU NVIDIA Tesla K40m)
- ✦ Reducing network size will reduce inference time.
- ✦ For comparison decoding time per event is ~15ms.









### GANs (pix2Pix)

The generative network

is trained to maximise the

final classification error.



One neural network, called the generator, generates new data instances, while the other, the discriminator, evaluates them for authenticity; i.e. the discriminator decides whether each instance of data that it reviews belongs to the actual training dataset or not.

Input random variables. The generated distribution and the true distribution are not compared directly. The discriminative network is trained to **minimise** the final classification error. The classification error is the basis metric for the training of both networks.











