

Deep Learning Techniques for Track Reconstruction in $\bar{\text{P}}\text{ANDA}$

Adeel Akram

Uppsala University
on behalf of the $\bar{\text{P}}\text{ANDA}$ Collaboration
adeel.akram@physics.uu.se

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Outline

- Conventional tracking approach
- Motivation for new methods
- Intro to Machine Learning
- Deep Learning
- Programing Frameworks
- Summary

Track Reconstruction

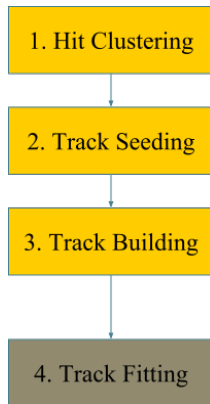
Common approach in Nuclear and Particle Physics (NPP):

Track finding

- Pattern recognition and/or classification
- Find tracklets
- Find ghost tracklets

Track fitting

- Input: tracklets
- Output: track kinematics



Track Reconstruction

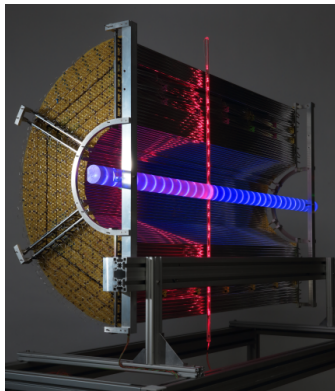
Conventional tracking methods suffer one or more of the following issues.
These models

- Rely on linear dynamic models
- Are serial in nature
- Scale badly with track multiplicity
- Consume huge computing resources

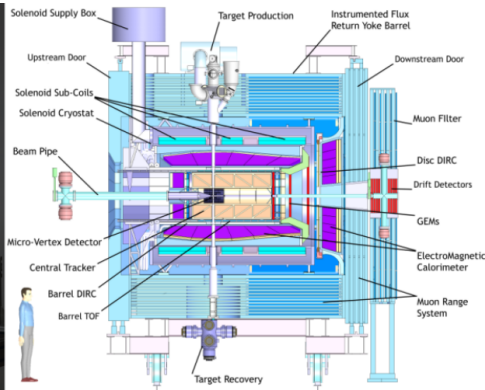
An alternate approach is using Machine Learning (ML) methods.

- Pattern recognition (*Track finding*)
- Extraction of track parameters (*Track fitting*)

PANDA Experiment



Straw Tube Tracker (STT)



Target Spectrometer

Earlier work in Deep Learning for $\overline{\text{PANDA}}$

Two student projects have been conducted at Uppsala University in 2017 using Deep Neural Networks. Two approaches has been used

- Standard DNNs with Supervised Learning
 - With 95% prediction accuracy
- Convolutional DNNs with Supervised Learning
 - With 80% prediction accuracy

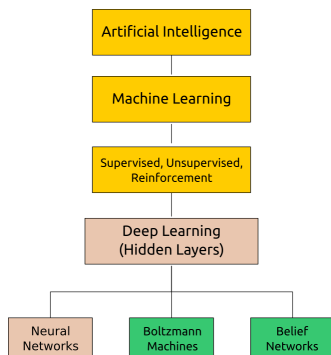
Machine Learning

Ability of machines to learn complex representations of data without explicitly programmed for this purpose.

Learning Schemes:

- Supervised Learning
 - Classification, Regression
- Unsupervised Learning
 - Clustering, Density Measurements
- Reinforcement Learning
 - Robotics etc

Deep Learning: Coming next...



Deep Learning

Standard Learning: Deep learning is an approach to introduce multiple hidden layers in the existing model. For example, we have

- Deep Neural Networks
 - Standard, Convolutional, Recurrent
- Deep Boltzmann Machines
- Deep Belief Networks

Adaptive Learning: Competitive hypotheses are introduced in a way that final outcome depends on current observation.

- Hopfield Neural Networks
- Elastic Nets
- Gaussian-sum filters

Deep Neural Networks (DNNs)

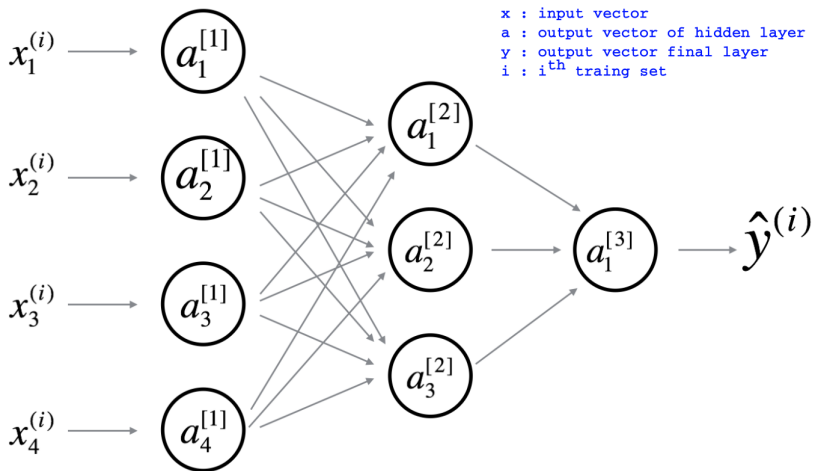


Figure: A three layered standard DNN

Mathematics of DNNs

Forward propagation:

$$z^{[l](i)} = W^{[l]} \cdot x^{(i)} + b^{[l]}$$

$$a^{[l](i)} = \text{ReLU}(z^{[l](i)})$$

$$\hat{y}^{(i)} = \hat{a}^{[l](i)}$$

Where,

z : linear equation

b : bias or intercepts

W : weight matrix

ReLU : **activation function**

a : output of l^{th} layer

\hat{y} : estimate of final layer

The prediction:

$$y_{prediction}^{(i)} = \begin{cases} 1, & \text{if } \hat{y}^{(i)} > 0.5 \\ 0, & \text{otherwise} \end{cases}$$

Loss Function:

$$L(\hat{y}^{(i)}, y^{(i)}) = -1/m \sum_i^m [\hat{y}^{(i)} \log(y_i) + (1 - \hat{y}^{(i)}) \log(1 - y_i)]$$

Mathematics of DNNs

Error backpropagation

Using method of gradient descent:

$$dW^{[l]} = \frac{\partial L}{\partial W^{[l]}}$$

$$db^{[l]} = \frac{\partial L}{\partial b^{[l]}}$$

$$da^{[l-1]} = \frac{\partial L}{\partial a^{[l-1]}}$$

$$dz^{[l]} = da^{[l]} \cdot g'(z^{[l]})$$

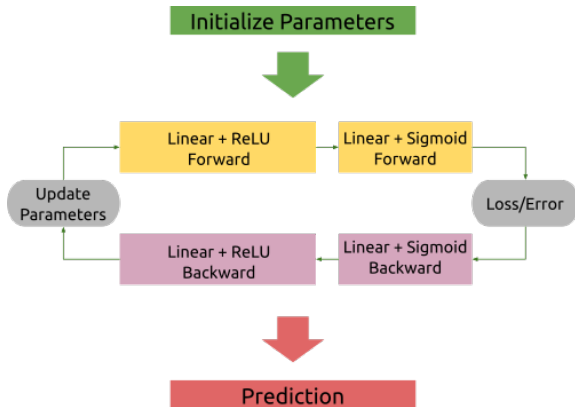
Parameter Update

Parameter update with the learning rate α :

$$W^{[l]} = W^{[l]} - \alpha dW^{[l]}$$

$$b^{[l]} = b^{[l]} - \alpha db^{[l]}$$

Flow Diagram



Programming Frameworks

C++ Environment:

- Standard C++/ROOT
- TMVA (Toolkit for Multivariate Analysis)
- etc.



Python Environment:

- Python 3.0
- Numpy for Vectorization
- TensorFlow/scikit-learn
- etc.



TrackML Competition 2018

 Featured Prediction Competition

TrackML Particle Tracking Challenge

High Energy Physics particle tracking in CERN detectors

 CERN · 300 teams · 3 months to go (2 months to go until merger deadline)

\$25,000
Prize Money

[Overview](#) [Data](#) [Kernels](#) [Discussion](#) [Leaderboard](#) [Rules](#) [Team](#) [My Submissions](#) [Submit Predictions](#)

Overview

Description

Evaluation

Prizes

About The Sponsors

Timeline

To explore what our universe is made of, scientists at CERN are colliding protons, essentially recreating mini big bangs, and meticulously observing these collisions with intricate silicon detectors.

While orchestrating the collisions and observations is already a massive scientific accomplishment, analyzing the enormous amounts of data produced from the experiments is becoming an overwhelming challenge.



Summary

- Earlier work has shown "promising" results
- Different learning schemes and DNN topologies should be investigated further
- DNNs can be expanded both for online and offline data processing

What Next

- Improvements on the earlier work
- Conversion from Matlab to TensorFlow
- Reproduce results using TensorFlow

Backup

Improving DNNs

Hyperparameters tuning

- Weights, bias, learning rate etc.

Regularization

- L2 Regularization
- Dropout Regularization

Optimization

- Adam Optimizer (used in PANDA, Stud. Project)
- Genetic Algorithm

Normalization

Additional Resources

CONNECTING THE DOTS 2018
4TH INTERNATIONAL WORKSHOP
20-22 MARCH 2018
UNIVERSITY OF WASHINGTON, SEATTLE, USA

HEP.TrkX

**Workshop on Intelligent Trackers (WIT)
2017**

**4th Machine Learning in HEP
Summer School
2018**