Deploying physics-informed neural networks for anomaly detection in particle physics

Dr. Makhamisa Senekane

Institute for Artificial Intelligence Systems, University of Johannesburg

Outline

Introduction

Introduction

The following topics will be covered in this talk:

- Anomaly detection in particle physics
- Physics informed neural networks
- The use of PINN for anomaly detection in particle physics

Motivation

- Anomaly detection can assist in the discovery of the new phenomena in particle physics
- Machine learning is well suited for anomaly detection tasks
- PINN; which embeds the known physical laws, is a worthy model to explore for anomaly detection in particle physics and hence aid in the discovery of the new physics

Background

Anomaly Detection in Particle Physics

- Theory-driven/traditional parametrized hypothesis formulation (challenge: Only targets known possibilities. It might miss some evidence of the new physics)
- Data-driven/machine learning-based (challenge: machine learning models are unaware of the laws of nature. Hence they might produce outcomes that violate the laws of nature)

Machine Learning (ML)

Enables computers to learn from data without being explicitly preprogrammed

ML Applications

Machine Learning applications include:

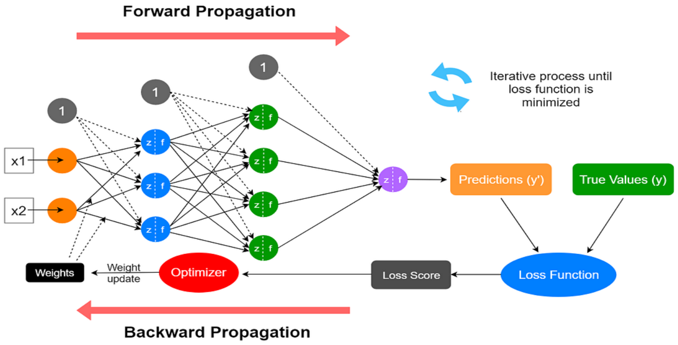
- Customer churn modeling
- Anomaly detection
- Recommender system
- Game design
- Science (ML for science)

Machine Learning - Models

Some of the Learning models include:

- Logistic Regression
- Support Vector Machine (SVM)
- Decision Trees
- Random Forest (RF)
- **Artificial Neural Network (ANN)**

ANN



Credit: https://www.linkedin.com/pulse/path-genai-power-neural-networks-carlo-consoli-u3ubf/

ANN Architectures

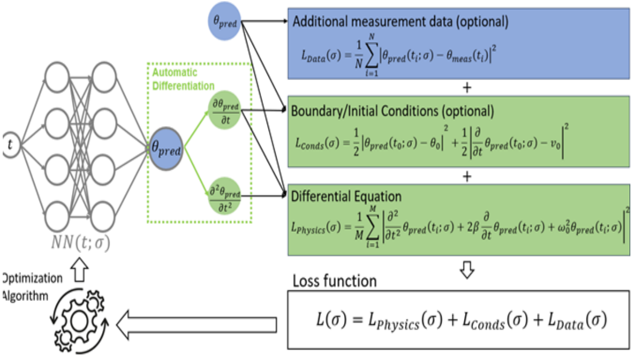
ANN architectures include:

- Multi-layer perceptron (MLP)
- Convolutional Neural Network (CNN)
- Recurrent Neural Network (RNN)
- Auto-encoder
- **PINN**

PINN

- ANN model that incorporates physics in the training process
- It is both data-driven and physics theory-guided (combines both the observational data and the laws of physics)
- PINN architecture works very well with sparse or noisy data

PINN



Credit: https://www.mathworks.com/discovery/physics-informed-neural-networks.html

ML Performance Metrics

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall(sensitivity) = \frac{TP}{TP + FN} \tag{3}$$

$$F_1 score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Methodology

Methodology

- Programming language: Python
- PINN library: DeepXDE
- PINN architecture: Physics-informed convolutional variational autoencoder (PIConVAE)
- Baseline model: Random Forest
- Dataset: CERN proton collision dataset (URL: https://www.kaggle.com/datasets/fedesoriano/multijet-primary-dataset/data)

Performance Metrics

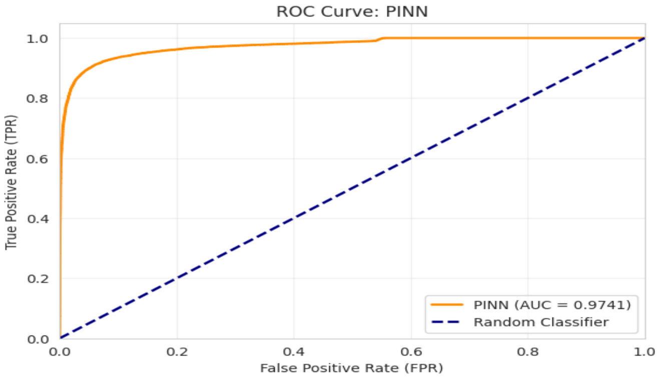
- F_1 score
- Precision
- Recall
- ROC-AUC

Results

Results

Performance Metric	Baseline (RF)	PINN
F_1 Score	0.79	0.92
Precision	0.83	0.94
Recall	0.95	0.91

Results - PINN ROC-AUC



Summary

Summary

In this talk, the following were covered:

- Anomaly detection in particle physics
- Physics informed neural networks
- The use of PINN for anomaly detection in particle physics
- PINN outperformed the baseline model in anomaly detection

Thank You

Questions?