



UiO : Fysisk institutt

Det matematisk-naturvitenskapelige fakultet

Application of Supervised Machine Learning to the Search for New Physics in ATLAS data

A Study of Ordinary Dense, Parameterized
and Ensemble Networks and their Application
to High Energy Physics

William Hirst

May 19, 2023

Outline

1 Overview

2 Introduction & Motivation

- Why apply machine learning to HEP problems?
- How do we search for new physics?

3 The Implementation

- A summary of the applied methods
- How are the methods compared?
- Training strategy

4 Methods & Results

5 Conclusion & Outlook

6 References

Overview

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Why apply machine learning to HEP problems?

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A summary of the applied methods

Three neural network variants

- Ordinary dense neural network
- Ensemble networks utilizing Local-Winner-Takes-All (LWTA) layers
- Parameterized neural networks (PNN)

One boosted decision tree method

- XGBoost using default settings

How are the methods compared?

Training strategy

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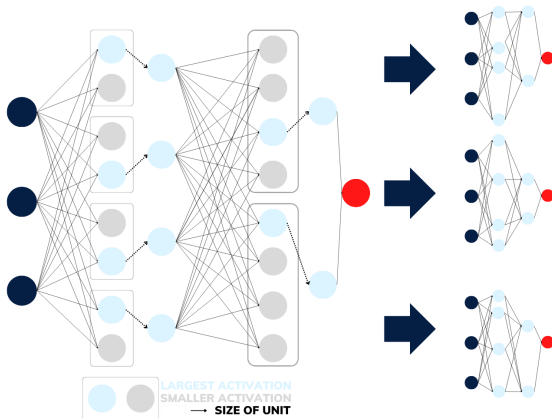
6 References

An introduction and study of each method

Ordinary dense neural network

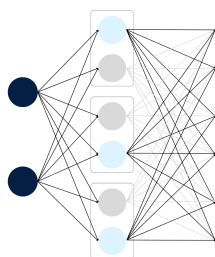
Ensemble methods - LWTA

- Dropout
- What is LWTA?
- Competing nodes - Units
- Encode information in pattern specific pathways

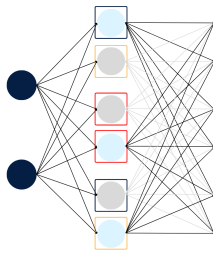


Channel-Out, SCO and Maxout

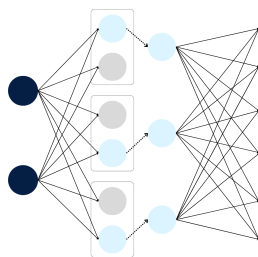
Layer	Separate Weights & Biases	Static Units
Channel-Out	Yes	Yes
SCO	Yes	No
Maxout	No	Yes



CHANNEL-OUT



SCO

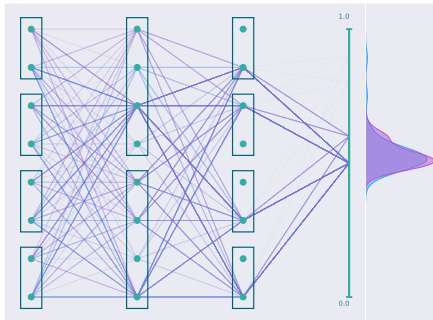


MAXOUT

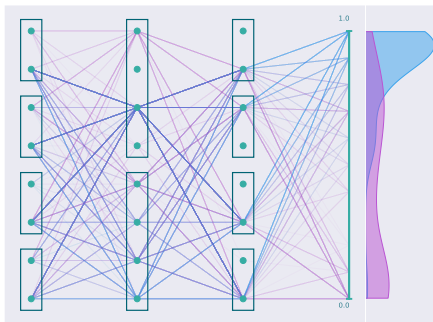
Visualization and study of sparse pathways

- A study of the implementation and effect of LWTA layers
- Visualize the activation and paths of 100 randomly sampled events
 - 50 background
 - 50 signal
- The bolder the line the more frequently the path is used.

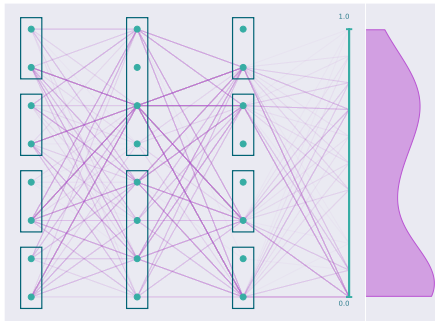
Before training



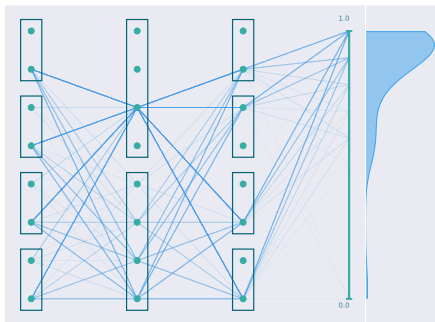
After training



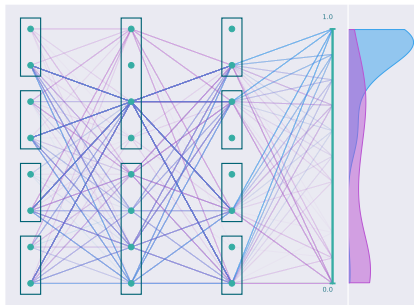
Background



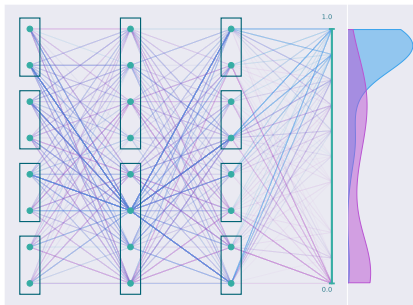
Signal



Comparing activation of Maxout with SCO



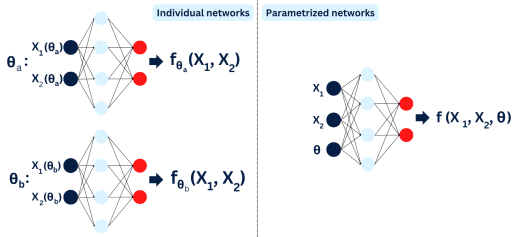
Maxout



SCO

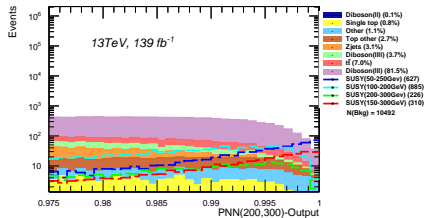
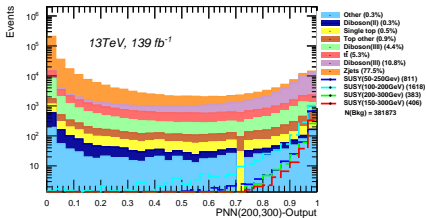
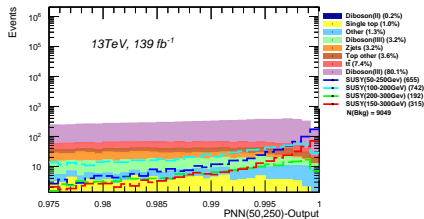
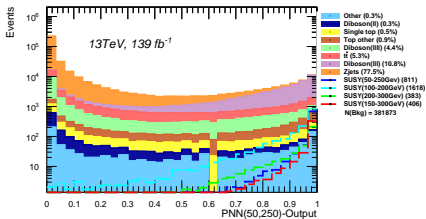
Parameterized neural network

- For diverse data set, X , dependent on a parameter, $X(\theta)$
 - Classical approach: One model for each parameter
 - PNN approach: Include θ as feature in feature set
- Signal events using masses $\{A, B\}_{GeV}$ to generate event during simulation will include the parameters A and B in feature set
- Background assigned parameters randomly using same distribution as signal
- Motivation
 - Network will associate parameters with trends in the data



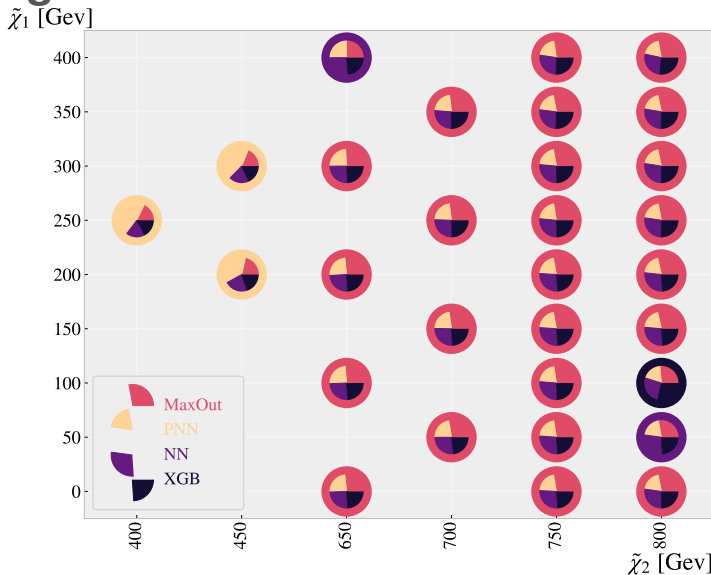
Study the effect of the parameters in the PNN

- Study if the parameters effect the training as intended
- Test: Manually assign all the events, both background and signal, the same parameters (mass combinations) thereby assigning most of the signal the wrong parameters
- Hypothesis: PNN performs better when events are assigned correct parameters
- First test: All events are given parameters $\{50, 250\}_{\text{GeV}}$
- Second test: All events are given parameters $\{200, 300\}_{\text{GeV}}$



Boosted decision trees - XGBoost

Comparing the sensitivity on a subset of the signal



Increasing sensitivity through a PCA

Comparing the methods to previous analysis

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