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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

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Outline

Overview

Outline

Why apply machine learning to HEP problems?

How do we search for new physics?

Outline

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

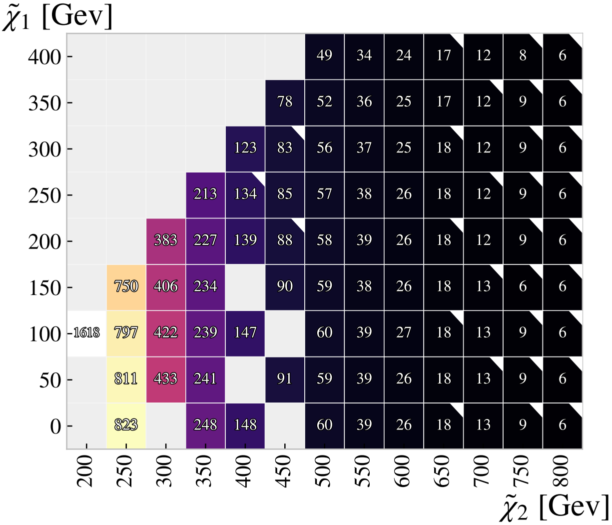
- XGBoost using default settings

How are the methods compared?

Training strategy

Mass combinations of the chargino-neutralino pair

- Full signal grid
  - 89 mass combinations
- Original signal set: white corners
  - 30 mass combinations
- The smaller the masses, the larger the contribution



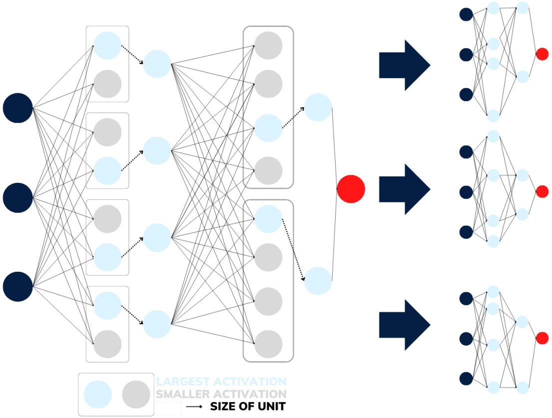
Outline

An introduction and study of each method

Ordinary dense neural network

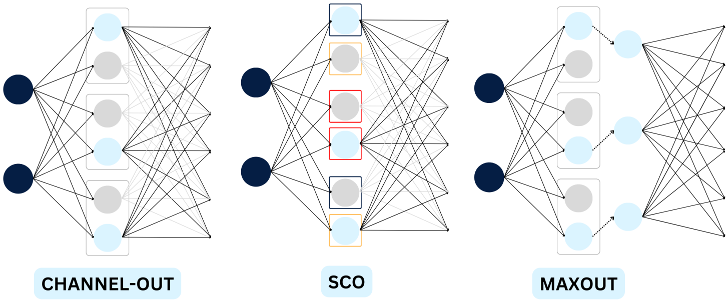
Ensemble methods - LWTA

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



Channel-Out, SCO and Maxout

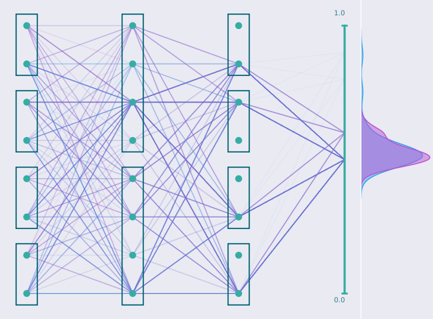
Layer	Separate Weights & Biases	Static Units
Channel-Out	*Yes*	*Yes*
SCO	*Yes*	*No*
Maxout	*No*	*Yes*



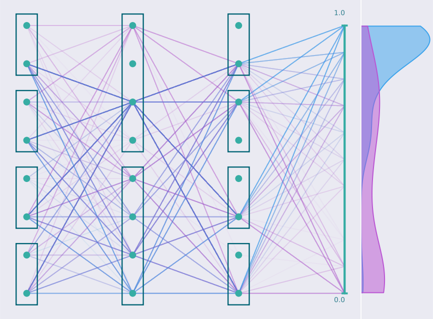
Visualization and study of sparse pathways

- 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.

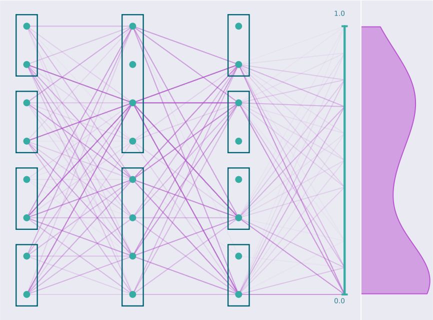
Before training



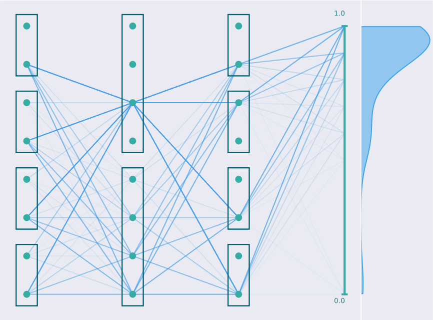
After training



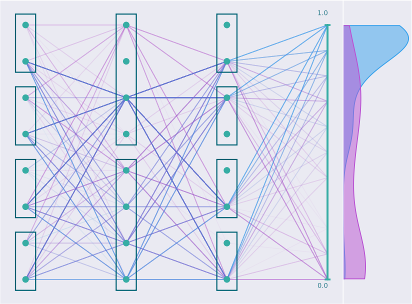
Background

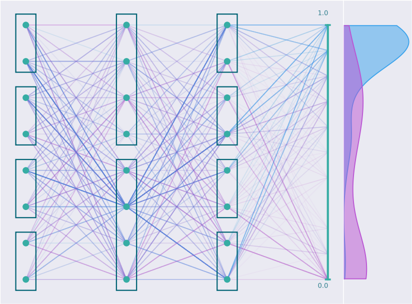


Signal



Comparing activation of Maxout with SCO

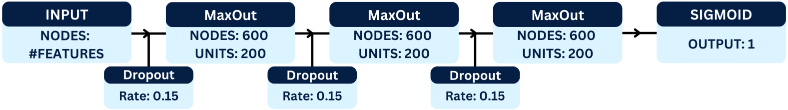




Maxout **SCO**

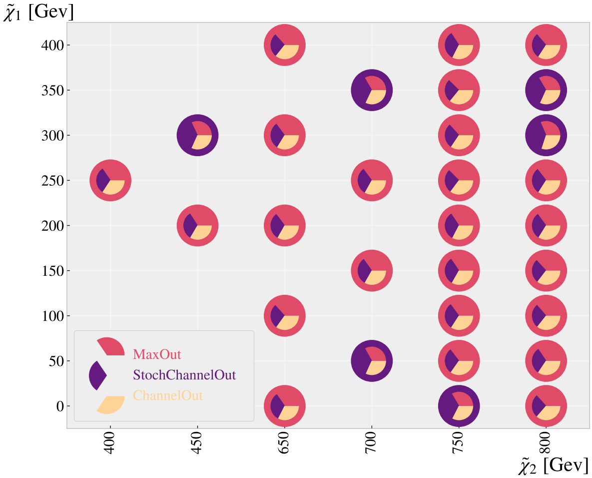
Ensemble network architecture

MaxOut:



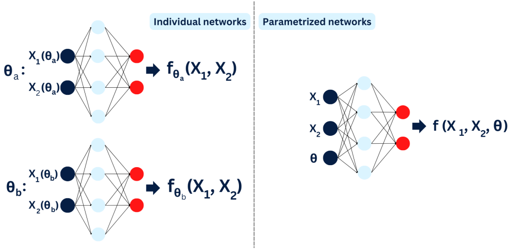
Comparing sensitivity of channel-out, SCO and maxout

- Maxout: 23/30
- SCO: 7/30
  - No trend for preferred masses
  - Possibly improve without layer on prediction

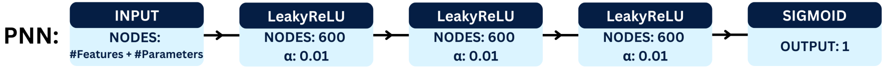


Parameterized neural network

- 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

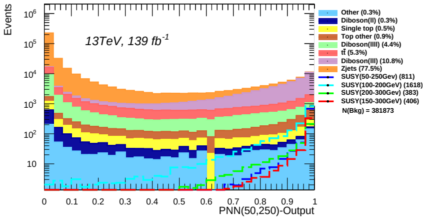


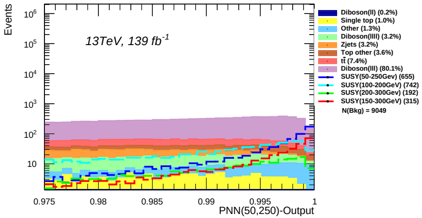
PNN architecture

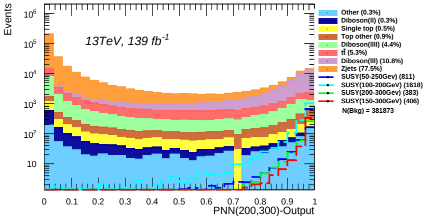


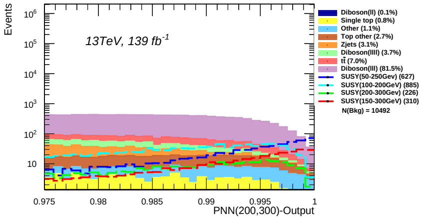
Study the effect of the parameters in the PNN

- 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 $\{50, 250\}_{GeV}$
- Second test: All events are given parameters $\{200, 300\}_{GeV}$


Events
13TeV, 139 fb^-1
Other (0.3%)
Diboson(II) (0.3%)
Single top (0.5%)
Top other (0.9%)
Diboson(IIII) (4.4%)
tt̄ (5.3%)
Diboson(III) (10.8%)
Zjets (77.5%)
SUSY(50-250Gev) (811)
SUSY(100-200GeV) (1618)
SUSY(200-300Gev) (383)
SUSY(150-300GeV) (406)
N(Bkg) = 381873
PNN(50,250)-Output


Events
13TeV, 139 fb^-1
Diboson(II) (0.2%)
Single top (1.0%)
Other (1.3%)
Diboson(IIII) (3.2%)
Zjets (3.2%)
Top other (3.6%)
tt̄ (7.4%)
Diboson(III) (80.1%)
SUSY(50-250Gev) (655)
SUSY(100-200GeV) (742)
SUSY(200-300Gev) (192)
SUSY(150-300GeV) (315)
N(Bkg) = 9049
PNN(50,250)-Output

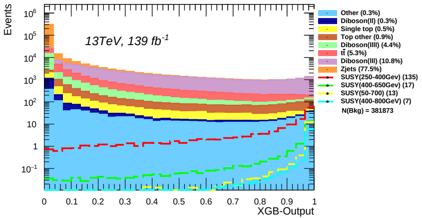

Events
13TeV, 139 fb^-1
Other (0.3%)
Diboson(II) (0.3%)
Single top (0.5%)
Top other (0.9%)
Diboson(IIII) (4.4%)
tt̄ (5.3%)
Diboson(III) (10.8%)
Zjets (77.5%)
SUSY(50-250Gev) (811)
SUSY(100-200GeV) (1618)
SUSY(200-300Gev) (383)
SUSY(150-300GeV) (406)
N(Bkg) = 381873
PNN(200,300)-Output

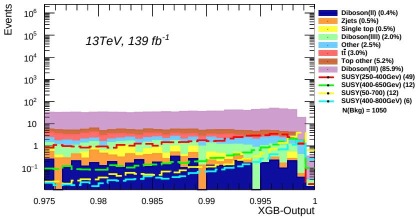

Events
13TeV, 139 fb^-1
Diboson(II) (0.1%)
Single top (0.8%)
Other (1.1%)
Top other (2.7%)
Zjets (3.1%)
Diboson(IIII) (3.7%)
tt̄ (7.0%)
Diboson(III) (81.5%)
SUSY(50-250Gev) (627)
SUSY(100-200GeV) (885)
SUSY(200-300Gev) (226)
SUSY(150-300GeV) (310)
N(Bkg) = 10492
PNN(200,300)-Output

Efficiency table

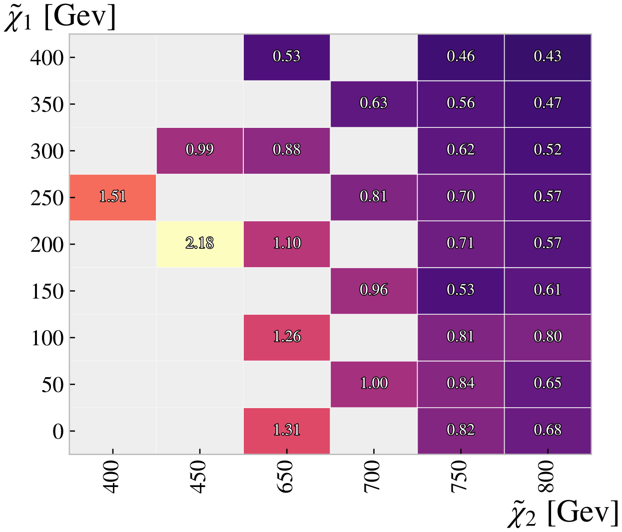
Channel / Parameters	$(50, 250)$	$(100, 200)$	$(150, 300)$	$(200, 300)$
$(50, 250)$	**80.8**%	45.8%	**77.5**%	50.1%
$(200, 300)$	77.3%	**54.6**%	76.3%	**59.0**%

Boosted decision trees - XGBoost

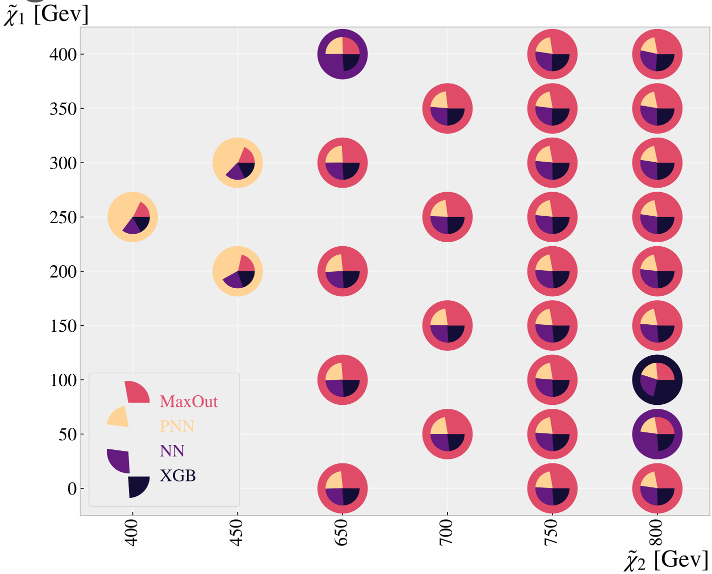




Sensitivity grid



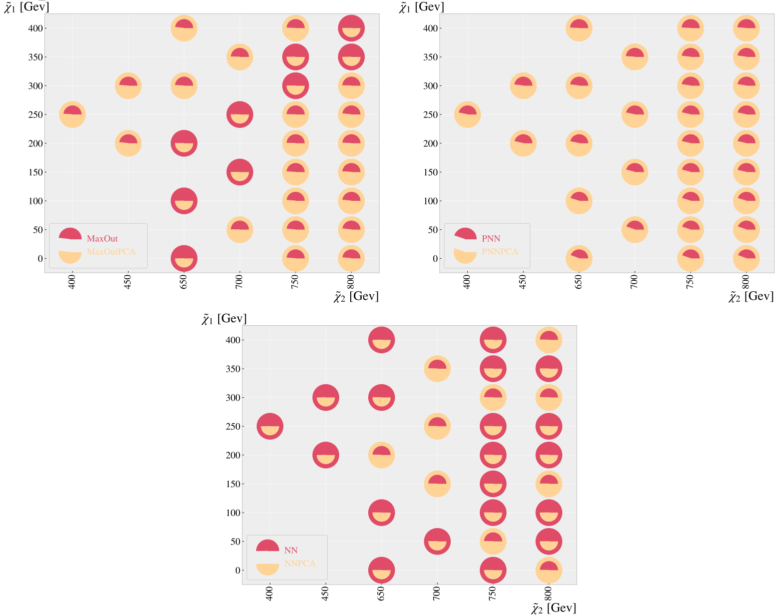
Comparing the sensitivity on a subset of the signal



Increasing sensitivity through a PCA

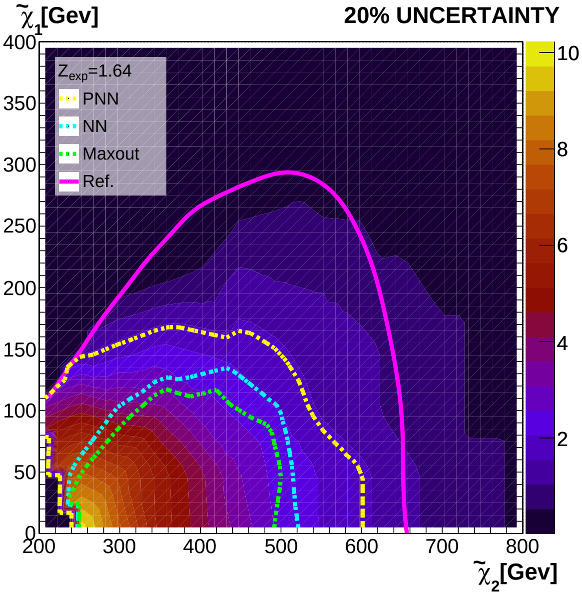
- What is PCA?
- Dimensionality reduction
- Creates new features using linear combination of original features
- Ranks from most to least variance
- This analysis
  - Demand conservation of 99.9% of variance/spread
  - 5 features removed

Compare methods with and without PCA

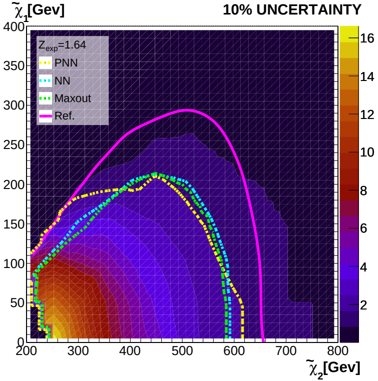


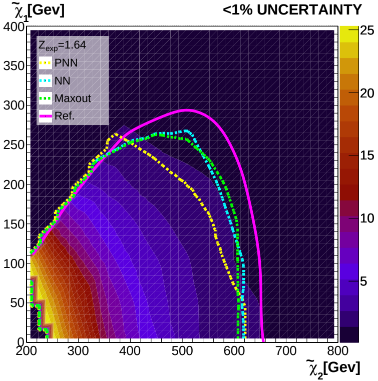
Comparing the methods to previous analysis

- Compare the expected limits of three best models to analysis made by ATLAS in 2021 [1]
- Introduce flat uncertainty for realistic comparison (20%, 10%, $< 1\%$)
- Include top performing methods
  - Maxout model with PCA
  - PNN with PCA
  - Ordinary dense neural network withou PCA



$\tilde{\chi}_1$[Gev]
20% UNCERTAINTY
Z_{exp}=1.64
PNN
NN
Maxout
Ref.
400
350
300
250
200
150
100
50
0
200
300
400
500
600
700
800
10
8
6
4
2
$\tilde{\chi}_2$[Gev]


$\tilde{\chi}_1$[Gev]
10% UNCERTAINTY
Z_{exp}=1.64
PNN
NN
Maxout
Ref.
$\tilde{\chi}_2$[Gev]


$\tilde{\chi}_1$[Gev]
<1% UNCERTAINTY
Z_{exp}=1.64
PNN
NN
Maxout
Ref.
$\tilde{\chi}_2$[Gev]

Outline

References I

ATLAS Collaboration.
'Search for chargino–neutralino pair production in final states with three leptons and missing transverse momentum in $\sqrt{s}$ = 13 TeV pp collisions with the ATLAS detector'.
http://arxiv.org/abs/2106.01676

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