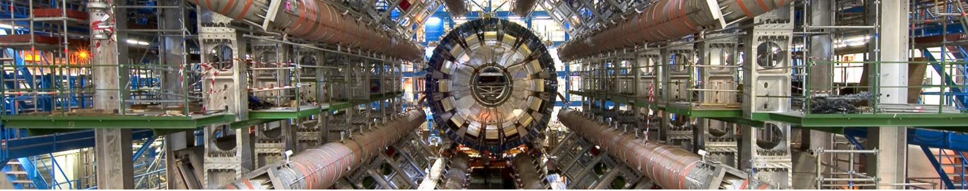

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Application of Supervised Machine Learning to the Search for New Physics in ATLAS data

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

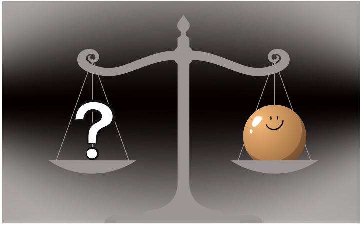
William Hirst

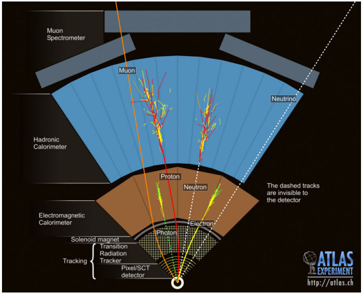
May 25, 2023

Outline

Why apply machine learning to HEP problems?

- The standard model (SM) of particle physics is very successful, but not complete
  - Neutrino masses
  - Hierarchy problem
- Large amount of data
- Machine learning (ML)
  - Event reconstruction
  - Particle classification
  - Creating search regions

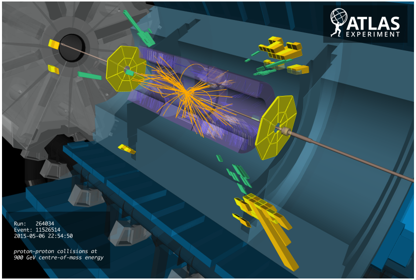


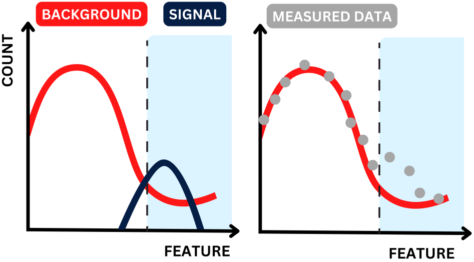


How do we search for new physics?

- Compare theory with experiment
  - Experiment: Measured
  - Theory: Simulated

- Search regions
- Expected significance
  - $Z_{exp} \approx \frac{signal}{\sqrt{background}}$
- Difficult to separate $\rightarrow$ ML



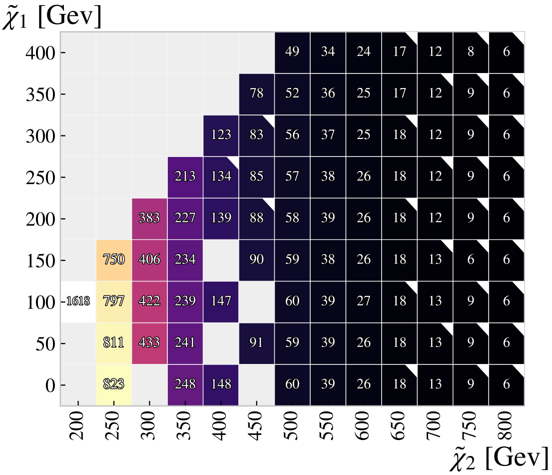


General aim of thesis

1. Signal $\rightarrow$ background
2. Use ML to separate signal from background
3. Study and compare

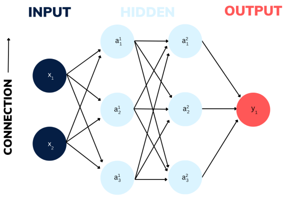
The SUSY signal

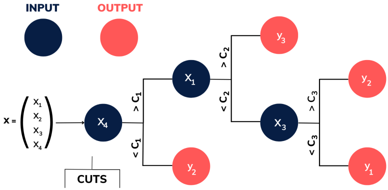
- Chargino-neutralino production
- Free parameters $\rightarrow$ masses
- Nr-of-Events(Mass)



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

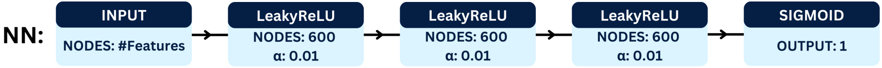




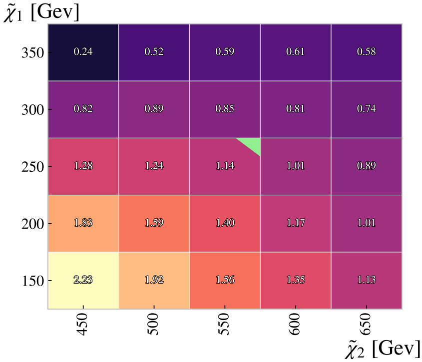
Training strategy

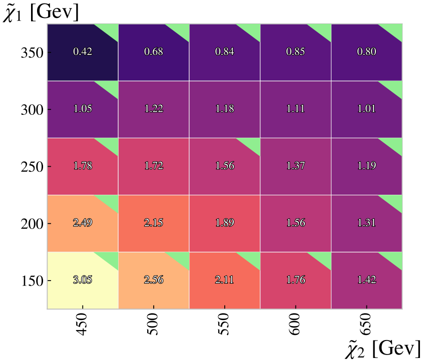
- Classification
  - Background $\rightarrow$ 0
  - Signal $\rightarrow$ 1
- 80% training and 20% validation
- Early stopping criteria
  - Train as long as performance on validation set improves
  - Patience 10 epochs
  - Reset weights to best epoch

'Traditional' dense neural network



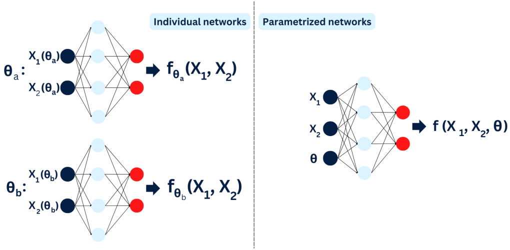
Compare one-mass approach to several-masses approach





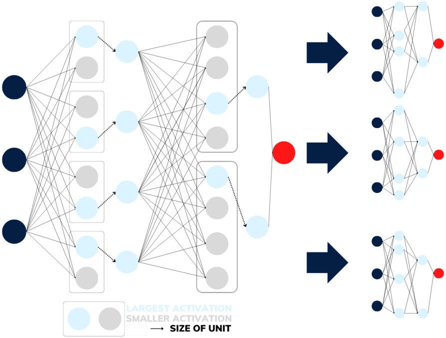
Parameterized neural network

- Long-term memory
- PNN $\rightarrow$ signal includes mass parameter in feature set
- Background assigned parameters randomly using same distribution as signal
- Motivation
  - Network will associate parameters with trends in the data



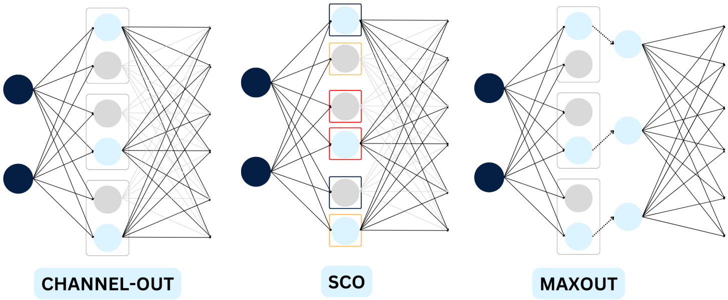
Ensemble methods - LWTA

- Local-Winnder-Takes-All
- Competing nodes - Units
- Encode information in pattern specific pathways



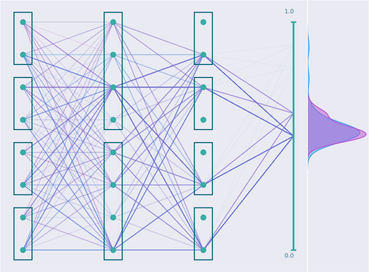
Channel-Out, SCO and Maxout

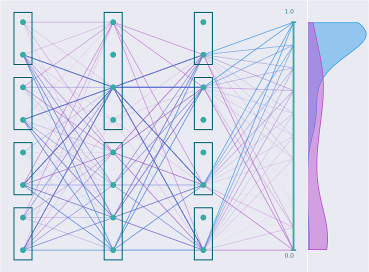
Layer	Separate weights	Static units
Channel-Out	✓	✓
SCO	✓	X
Maxout	X	✓



Visualization and study of sparse pathways

- Visualize the activation and paths of randomly sampled events
- The bolder the line the more frequently the path is used.
- Color of lines
    - Pink: SM background
    - Blue: SUSY signal





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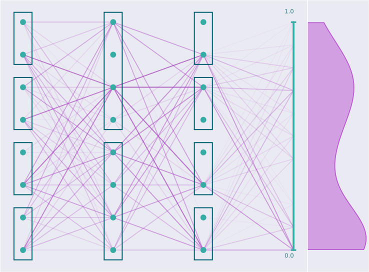
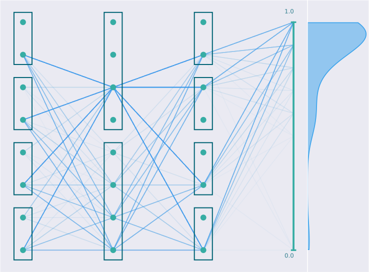
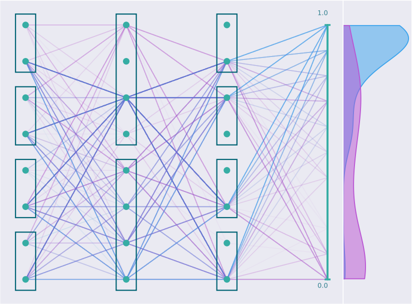
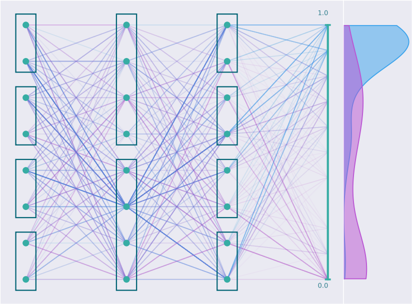




Comparing activation of Maxout with SCO



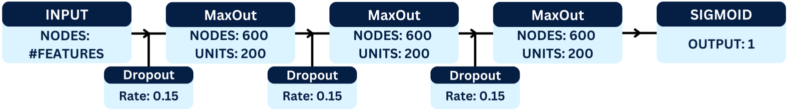
Maxout



SCO

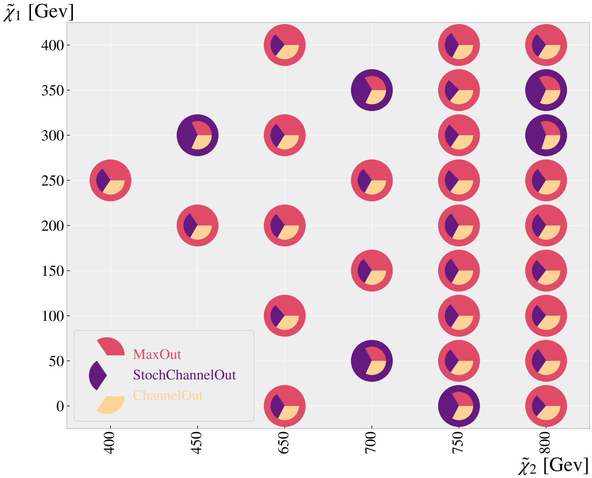
Ensemble network architecture

MaxOut:

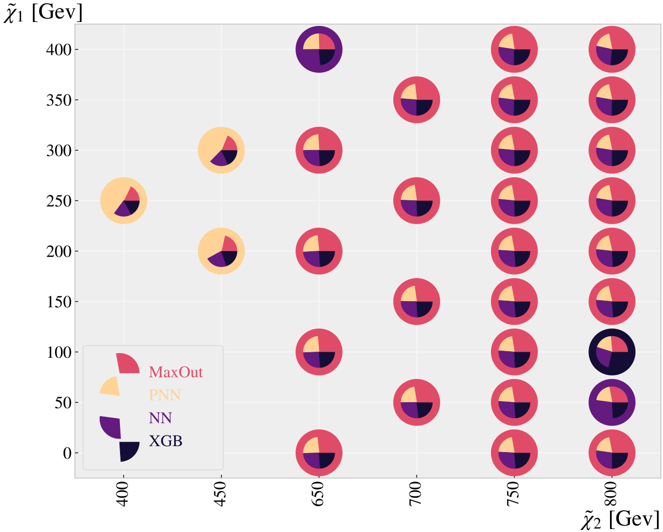


Comparing sensitivity of channel-out, SCO and maxout

- Maxout: 24/30
- SCO: 6/30
    - No trend for preferred masses
    - Possibly improve without layer on prediction



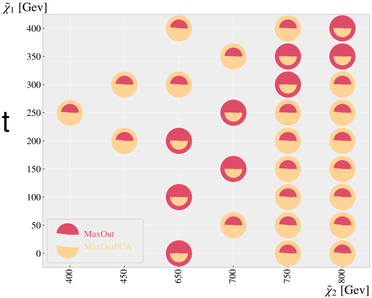
Comparing the sensitivity on a subset of the signal

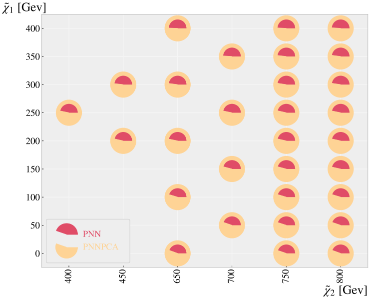


Increasing sensitivity through a PCA

- Dimensionality reduction
- This analysis
  - Demand conservation of 99.9% of variance/spread
  - 5 features removed

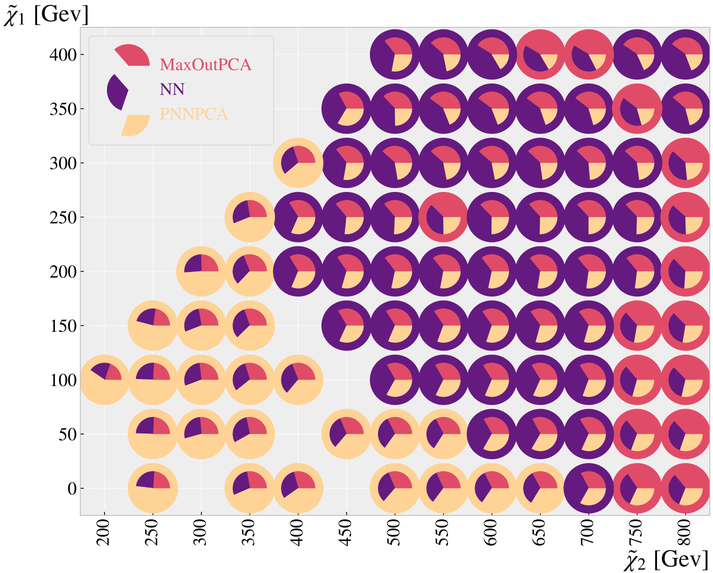
Maxout





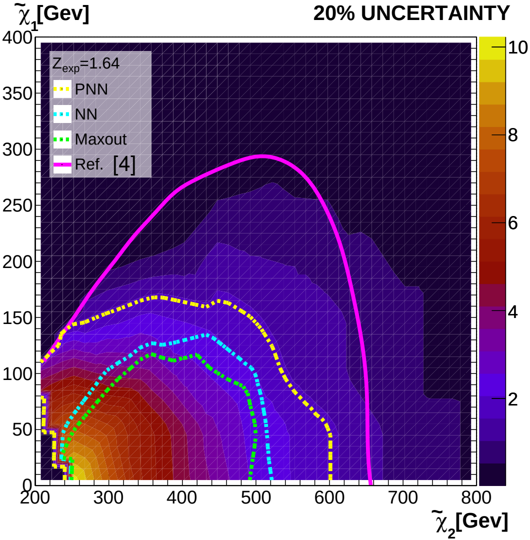
PNN

Comparing methods on full signal grid



Comparing the methods to previous analysis

- Compare the expected limits to analysis made by ATLAS in 2021 [4]



Conclusion & Outline

Key findings

1. Diverse signal $\rightarrow$ improve performance
2. PCA $\rightarrow$ improve performance of PNN and maxout
3. PNN bias towards smaller masses
4. Maxout achieved balanced performance

The way forwards

1. More advanced analysis of ML output
2. LWTA promising (SCO)
3. Combine PNN and LWTA

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Figure on slide 4

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