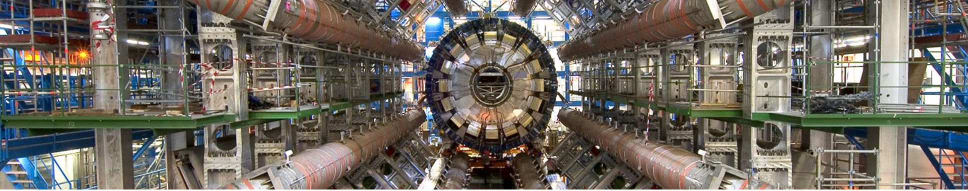

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Application of Supervised Machine Learning to the Search for New Physics in ATLAS data

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

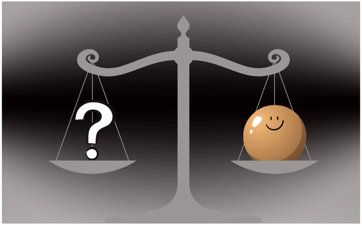
William Hirst

May 31, 2023

Outline

Why apply machine learning to HEP problems?

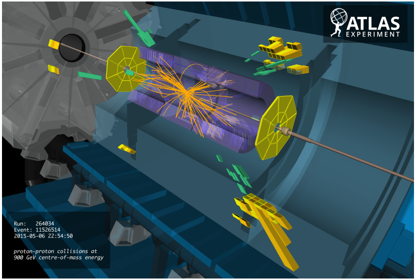
- The standard model (SM) is successful, but not enough
- Large amount of data
- Machine learning (ML)



How do we search for new physics?

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

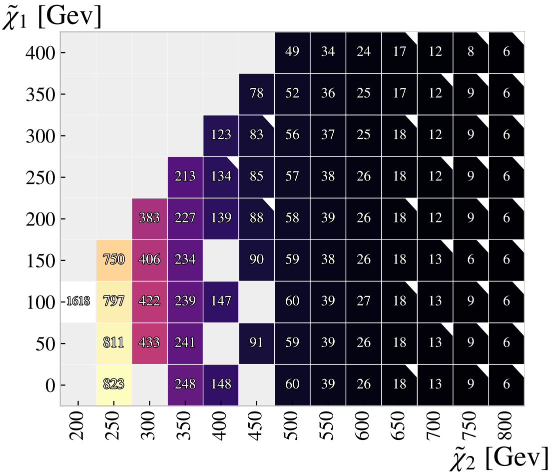
- Search regions
- Expected significance
  - $Z_{exp} \approx \frac{signal}{\sqrt{background}}$
- Difficult to separate $\rightarrow$ ML



Aim

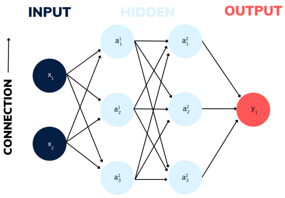
1. Signal $\rightarrow$ background
2. Use ML to separate signal from background
3. Measure performance in Z_{exp}
4. Study and compare

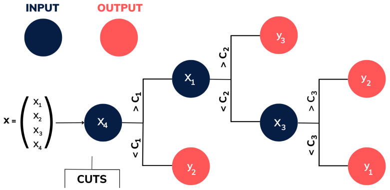
- Chargino-neutralino production
- Free parameters → masses
- Nr-of-Events(Mass)



A summary of the applied methods

- *Three* neural network variants
  - Ordinary dense neural network
  - Ensemble networks/Local-Winner-Takes-All (LWTA)
  - Parameterized neural networks (PNN)
- *One* boosted decision tree method

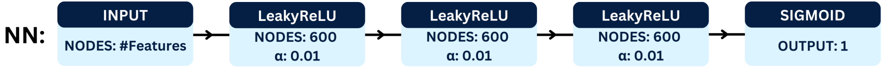




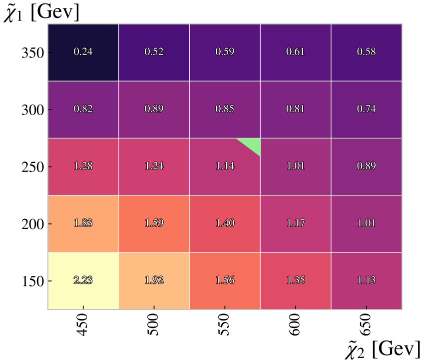
Training strategy

- Classification
  - Background $\rightarrow$ 0
  - Signal $\rightarrow$ 1
- 80% training and 20% validation
- Early stopping criteria
  - Performance on validation set

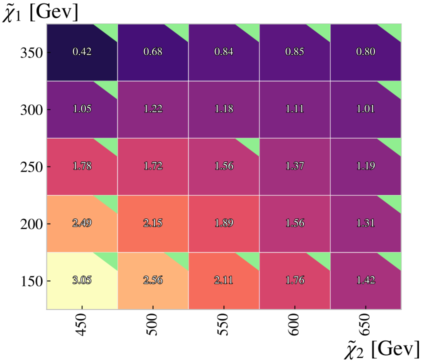
“Ordinary” dense neural network



Compare one-mass approach to several-masses approach



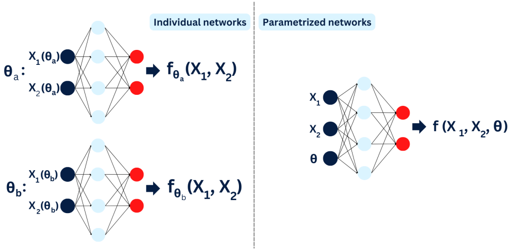
One-mass-model (OMM)



Several-mass-model (SMM)

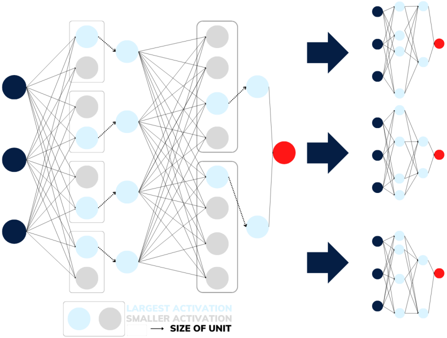
Parameterized neural network

- Long-term memory
- PNN $\rightarrow$ signal includes mass parameter in feature set
- Background assigned parameters randomly

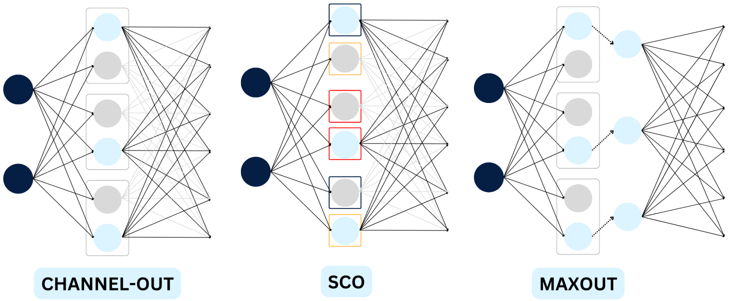


Ensemble methods - Local-Winner-Takes-All (LWTA)

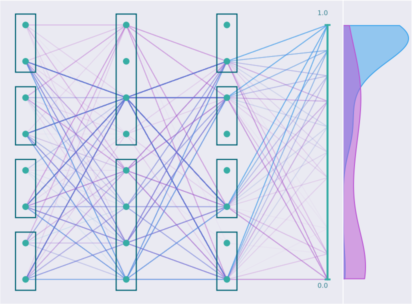
- Dropout
- Competing nodes - Units
- Encode information in pattern specific pathways



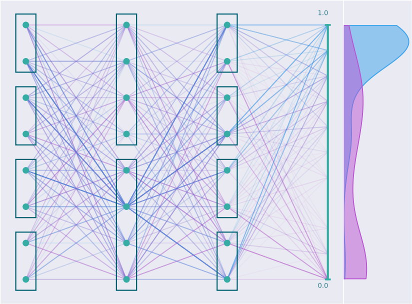
Channel-Out, Maxout and SCO



Visualization and study of sparse pathways

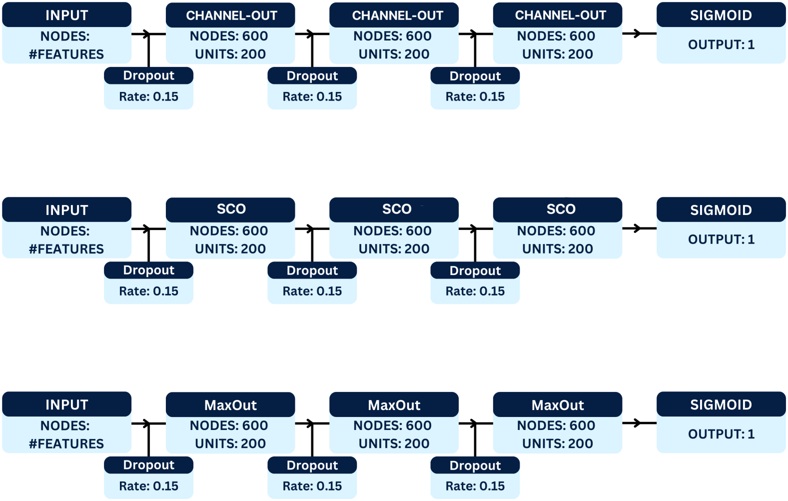


Maxout

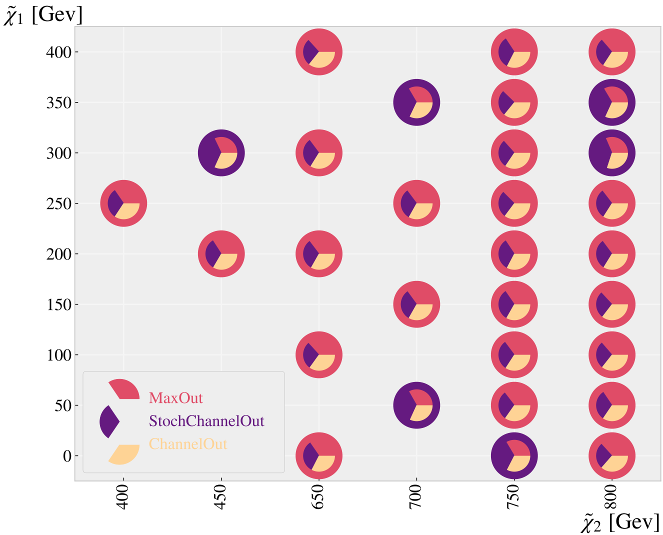


SCO

Ensemble network architecture

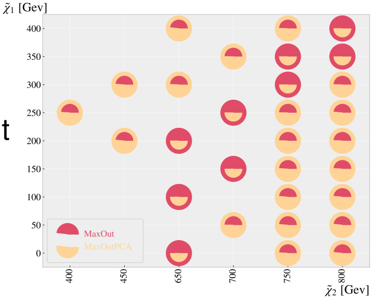


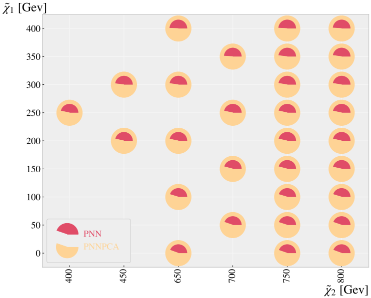
Comparing sensitivity of channel-out, SCO and maxout



Increasing sensitivity using principal component analysis

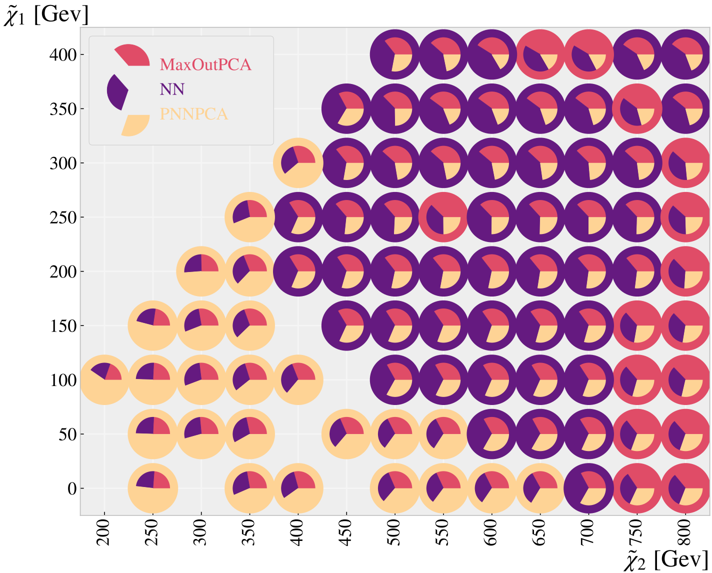
Maxout





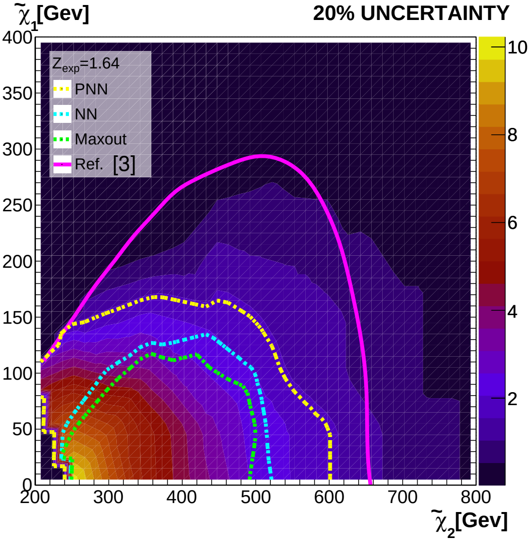
PNN

Comparing methods on full signal grid



Comparing the methods to previous analysis

- Compare the expected limits to analysis made by ATLAS in 2021 [3]



Conclusion & Outlook

Key findings

1. Diverse signal $\rightarrow$ improve performance
2. SCO
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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ATLAS Collaboration.
'ATLAS event at 900 GeV - 6 May 2015 - Run 264034 lb 659 event 11526514'.
https://cds.cern.ch/record/2015238
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ATLAS Collaboration [3].
'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