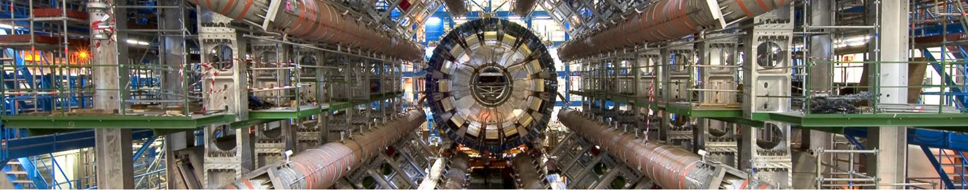


UiO Department of Physics
University of Oslo

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

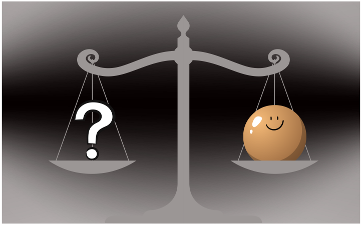
A Study of Ordinary Dense, Parameterized and Ensemble Networks and their Application to High Energy Physics

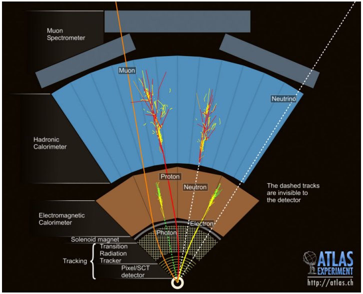
William Hirst **May 25, 2023**

Outline

Why apply machine learning to HEP problems?

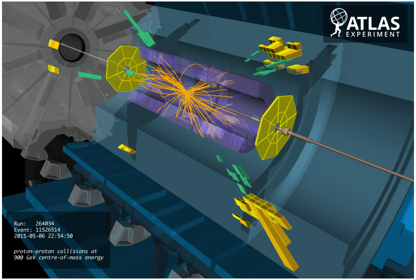
- The standard model (SM) of particle physics is very successful, but not complete
  - Neutrino masses
  - Hierarchy problem
- Large amount of data
- Machine learning (ML)
  - Event reconstruction
  - Particle classification
  - Creating search regions

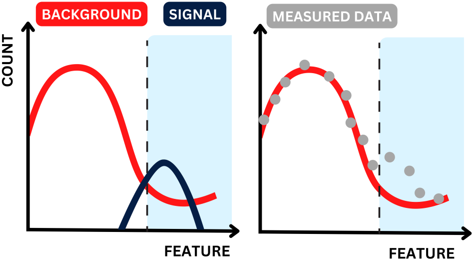




How do we search for new physics?

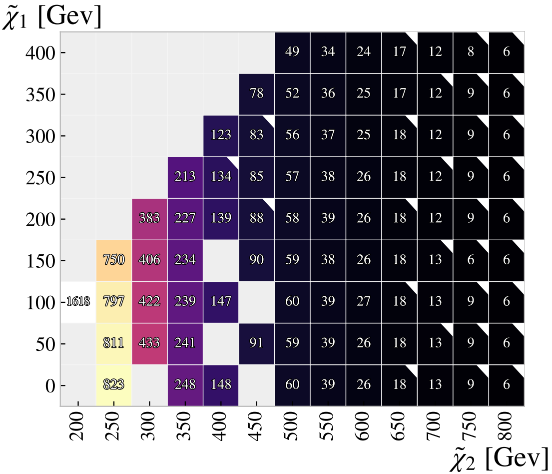
- Compare theory with experiment
  - Experiment: Measured
  - Theory: Simulated (background and signal)
- Search regions
- Expected significance
  - $Z_{exp} \approx \frac{signal}{\sqrt{background}}$
- Difficult to separate $\rightarrow$ ML



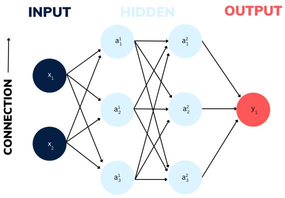


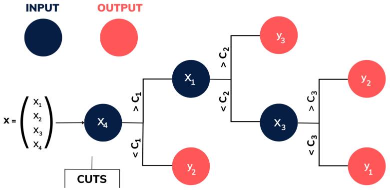
The SUSY signal

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



- *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





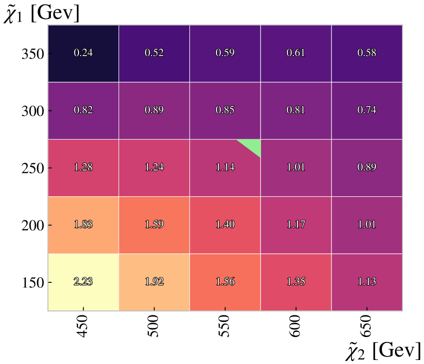
Training strategy

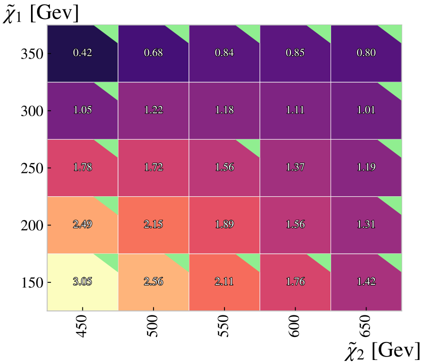
- Objective
  - Background $\rightarrow$ 0
  - Signal $\rightarrow$ 1
- 80% training and 20% validation
- Early stopping criteria
  - Train as long as performance on validation set improves
  - Patience 10 epochs
  - Reset weights to best epoch

Ordinary dense neural network

NN:

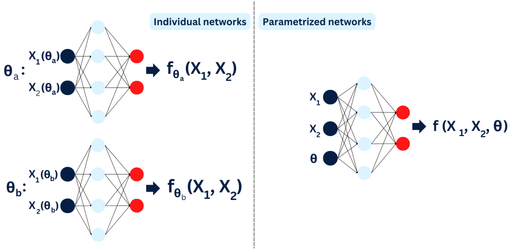
Compare one-mass approach to several-masses approach





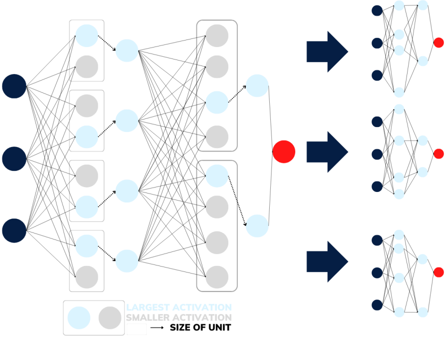
Parameterized neural network

- 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



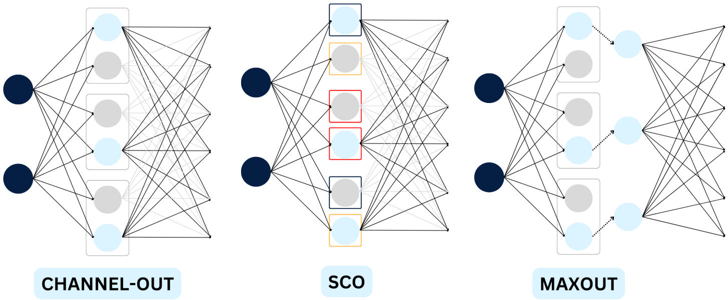
Ensemble methods - LWTA

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



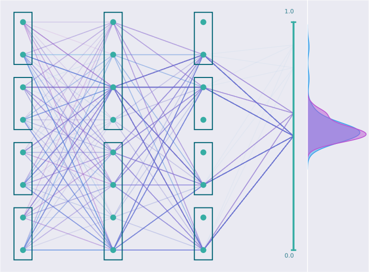
Channel-Out, SCO and Maxout

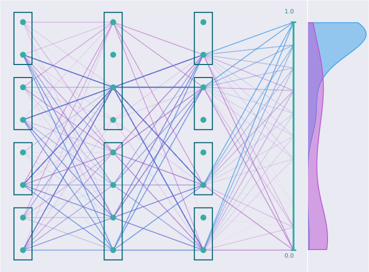
Layer	Separate weights	Static units
Channel-Out	✓	✓
SCO	✓	X
Maxout	X	✓



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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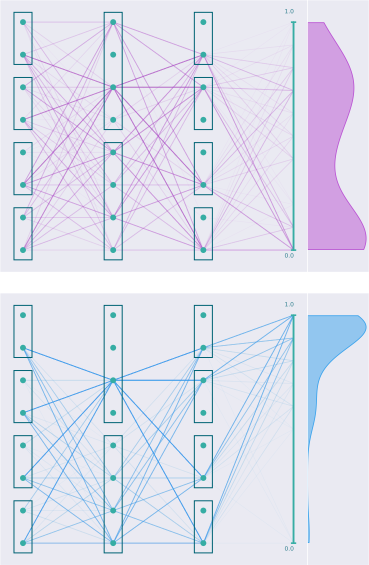
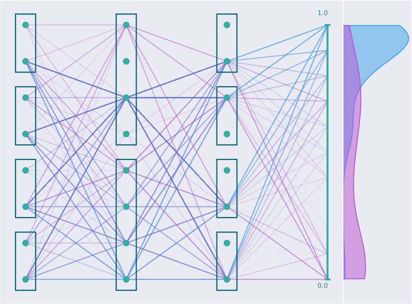
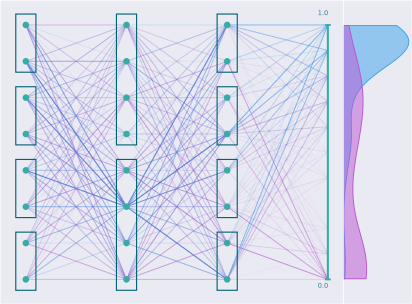


Comparing activation of Maxout with SCO



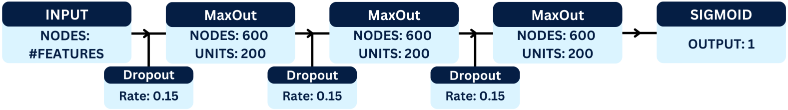
Maxout



SCO

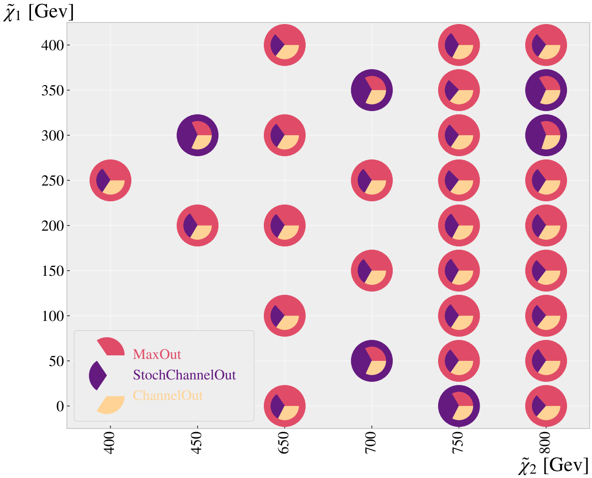
Ensemble network architecture

MaxOut:

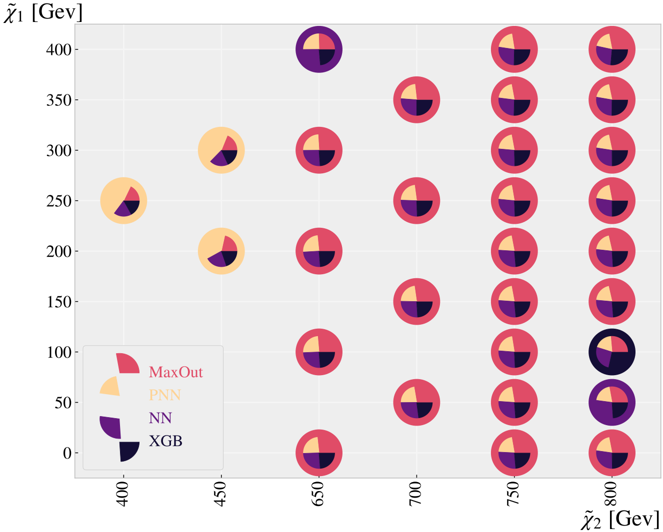


Comparing sensitivity of channel-out, SCO and maxout

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



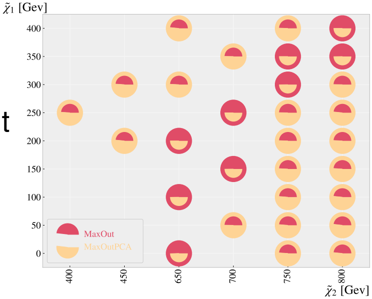
Comparing the sensitivity on a subset of the signal

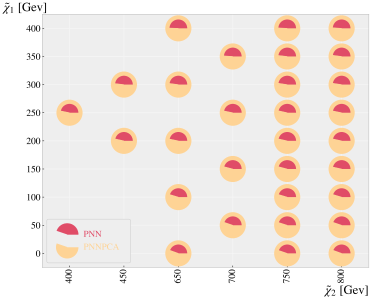


Increasing sensitivity through a PCA

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

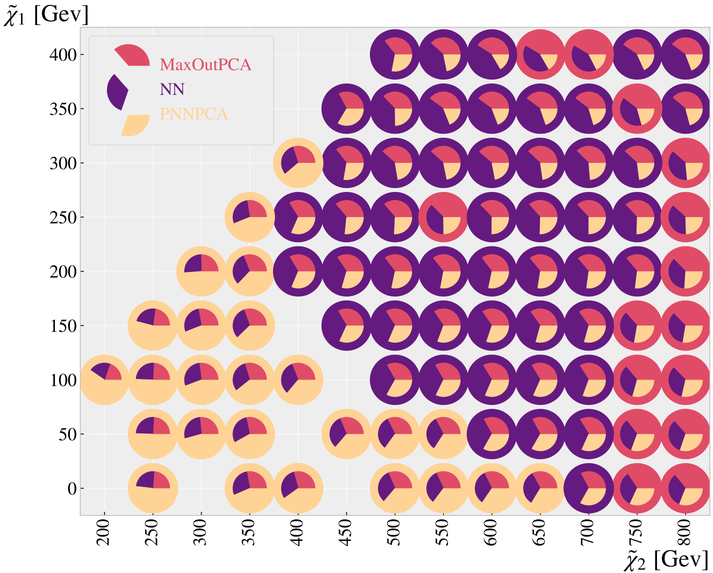
Maxout





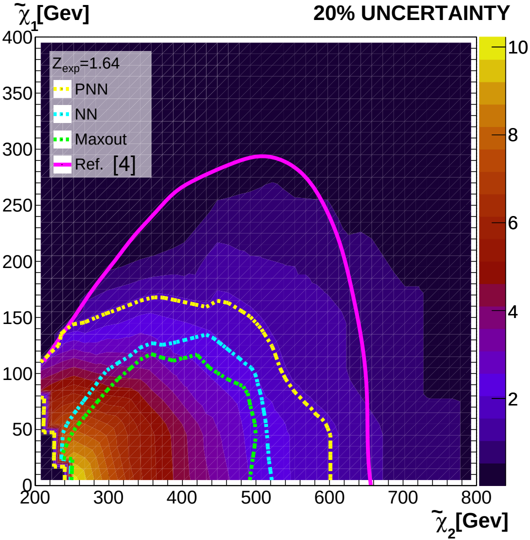
PNN

Comparing methods on full signal grid



Comparing the methods to previous analysis

- Compare the expected limits to analysis made by ATLAS in 2021 [4]
- Introduce flat uncertainty (20%, 10%, $< 1\%$)
- Why not better sensitivity?



Conclusion & Outlook

1. Including a diverse signal set can improve performance
2. The LWTA layers improve long-term memory via pattern specific pathways
3. PCA increased sensitivity of PNN and maxout model in original signal set
4. None of the networks extended expected limit past previous ATLAS analysis
5. PNN exhibited bias towards lower masses, whereas maxout model achieved a more balanced sensitivity
6. Long-term memory of LWTA layers is promising in future analysis where higher masses are studied

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