Electron identification with deep neural networks in the DAMPE experiment

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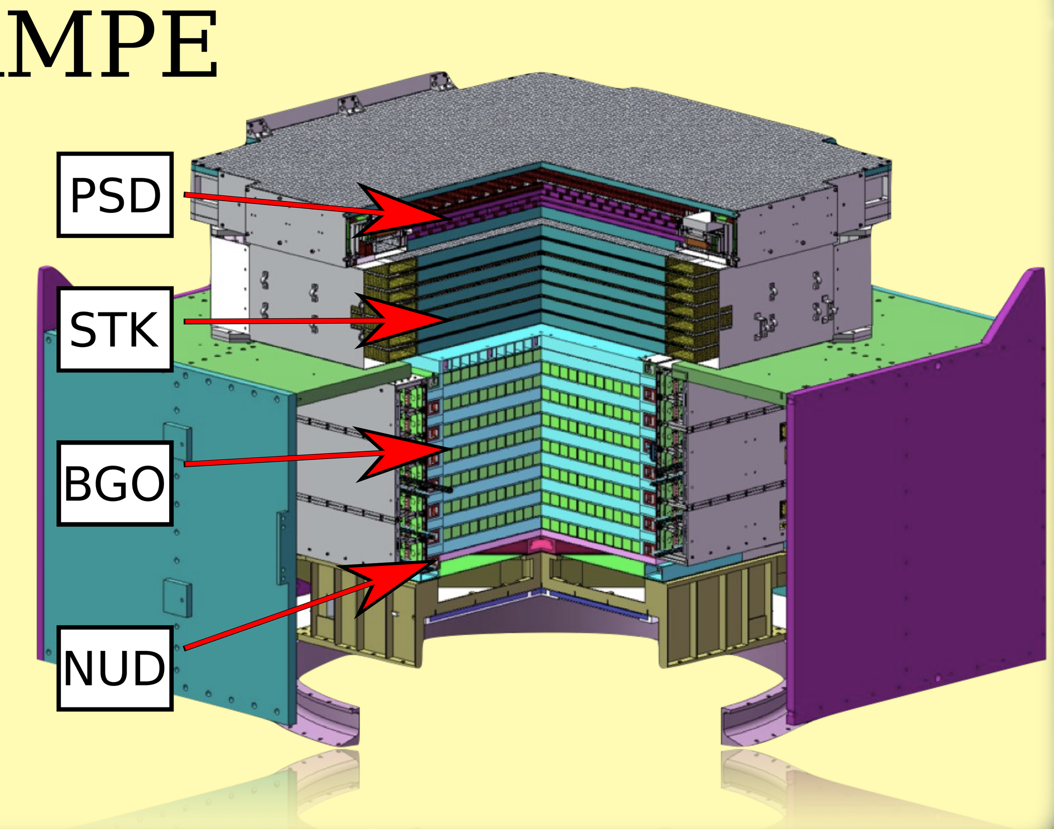
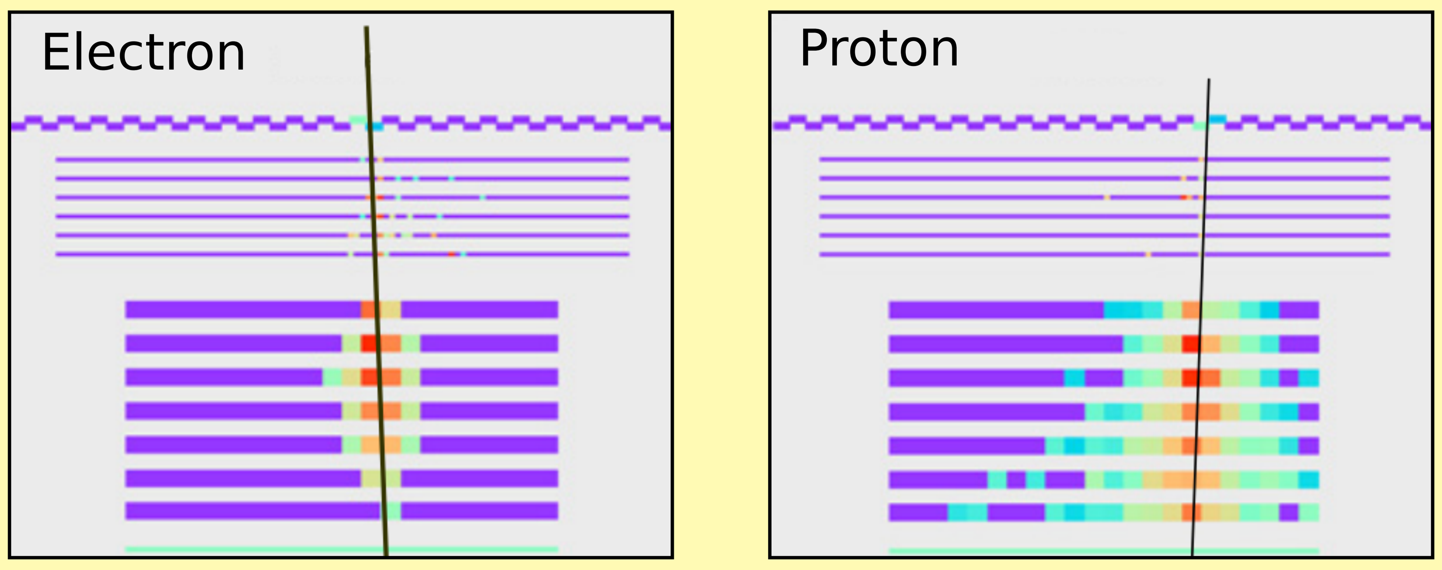
DArk Matter Particle Explorer - DAMPE

- Cosmic and gamma rays detector on sun-synchronous orbit since December 2015
- Result of a collaboration between institutes in China, Italy, Switzerland
- Four subdetectors:
  - Plastic Scintillator Detector (PSD) : anti-coincidence, Z measurement
  - Silicon TracKer converter (STK) : Tracking, photon conversion
  - Bismuth-Germanium Oxyde (BGO) calorimeter: ~32 X_0 used for identification, energy measurement, direction, trigger
  - NeUtron Detector (NUD): detects neutrons from hadronic showers
- Detects e+γ up to 10 TeV, resolution <2% at >10 GeV. ~40% for protons
- Base observable: deposited energy at position X, Y, Z



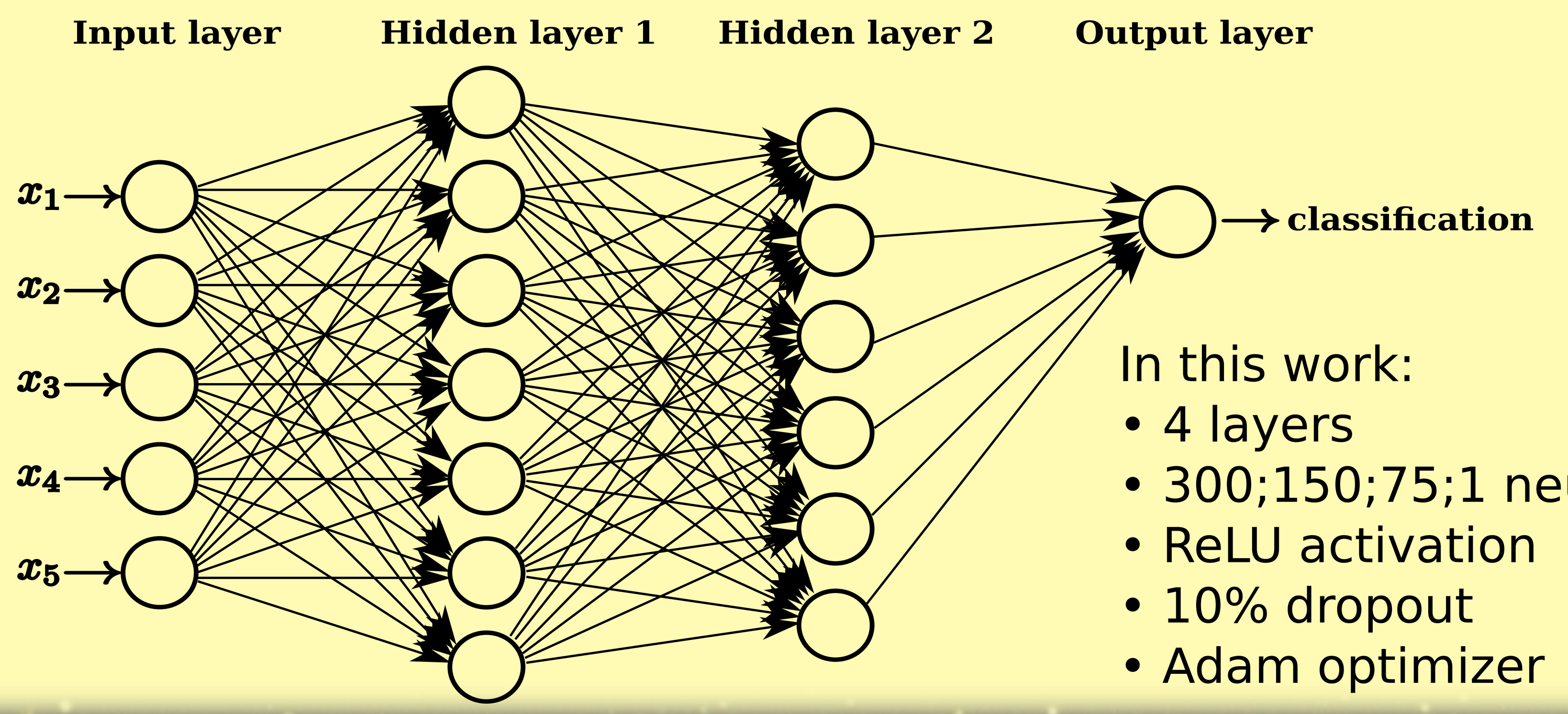
Electron - proton separation

- Protons outnumber electrons by >10² @1 TeV
- Protons leave a wider shower in calorimeter
- Particles leave similar signals at very high energies, need powerful multi-variate classifiers
- Cut-based analysis challenging at high energies



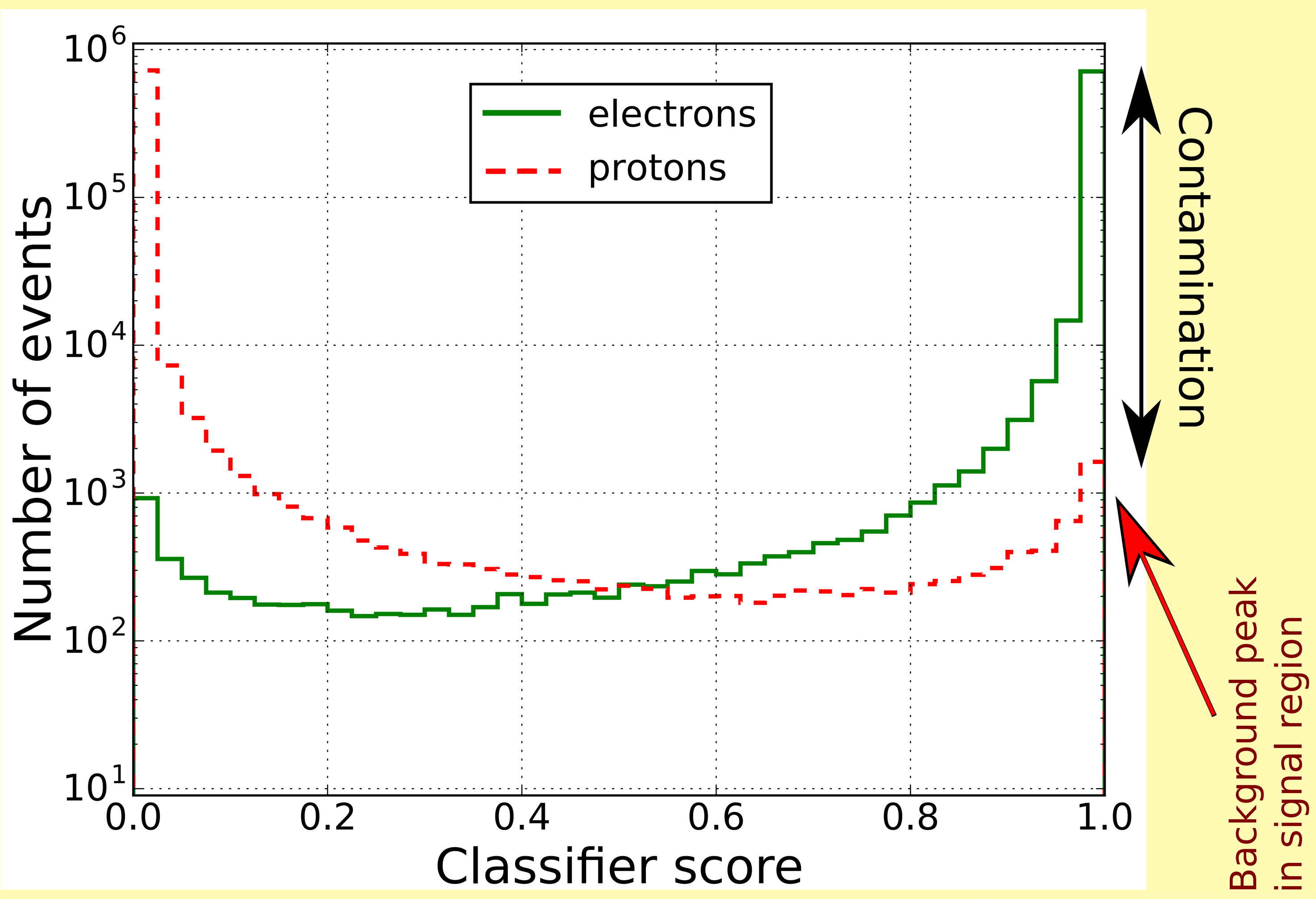
Deep Learning - a new old technique

- Neural Networks: 1950s idea, resurrected by modern computing
- Multi-variate technique, learns complex non-linear functions
- Powerful classifier, only seldomly used in astroparticle physics

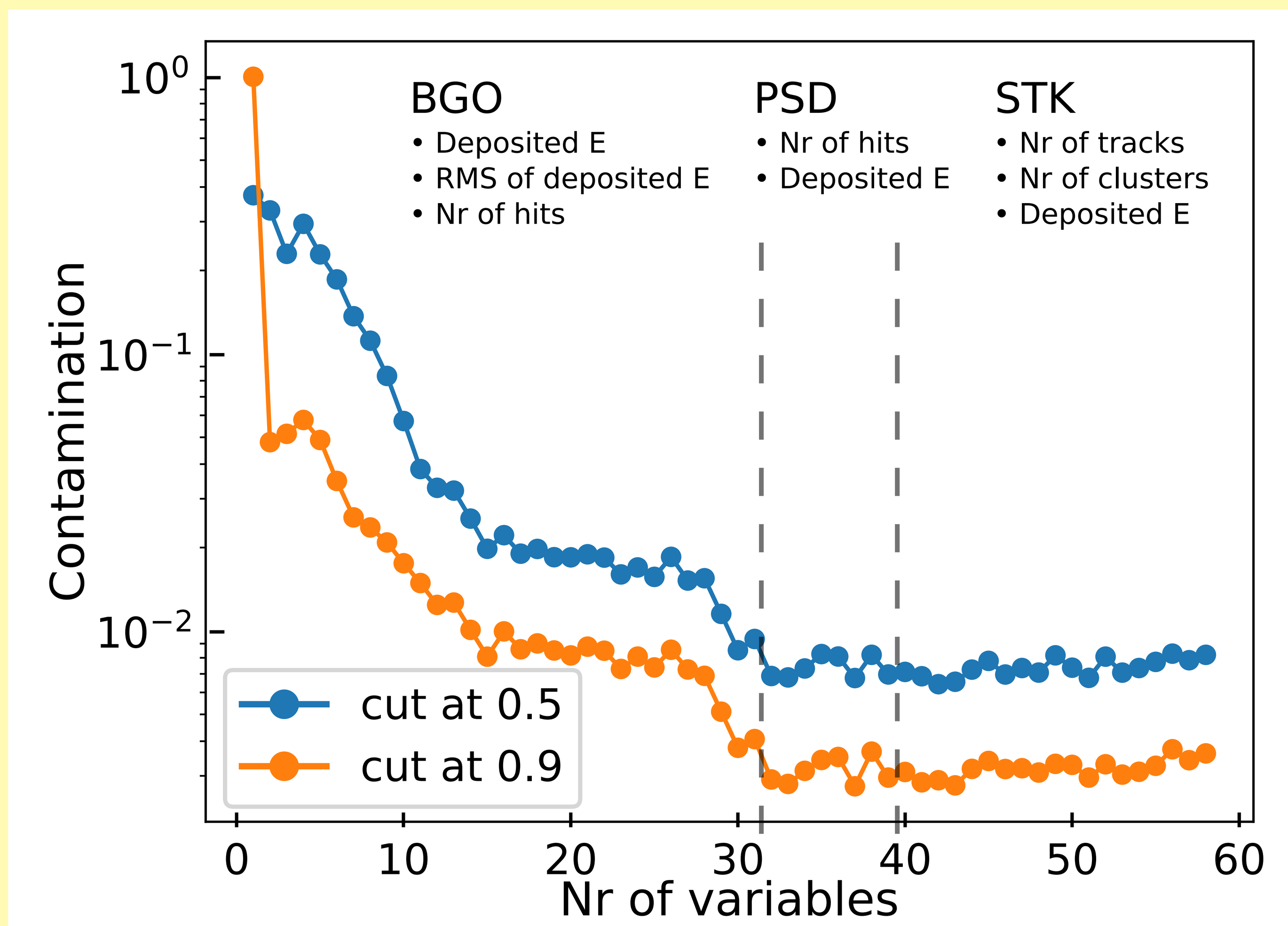


In this work:
- 4 layers
- 300;150;75;1 neurons
- ReLU activation
- 10% dropout
- Adam optimizer

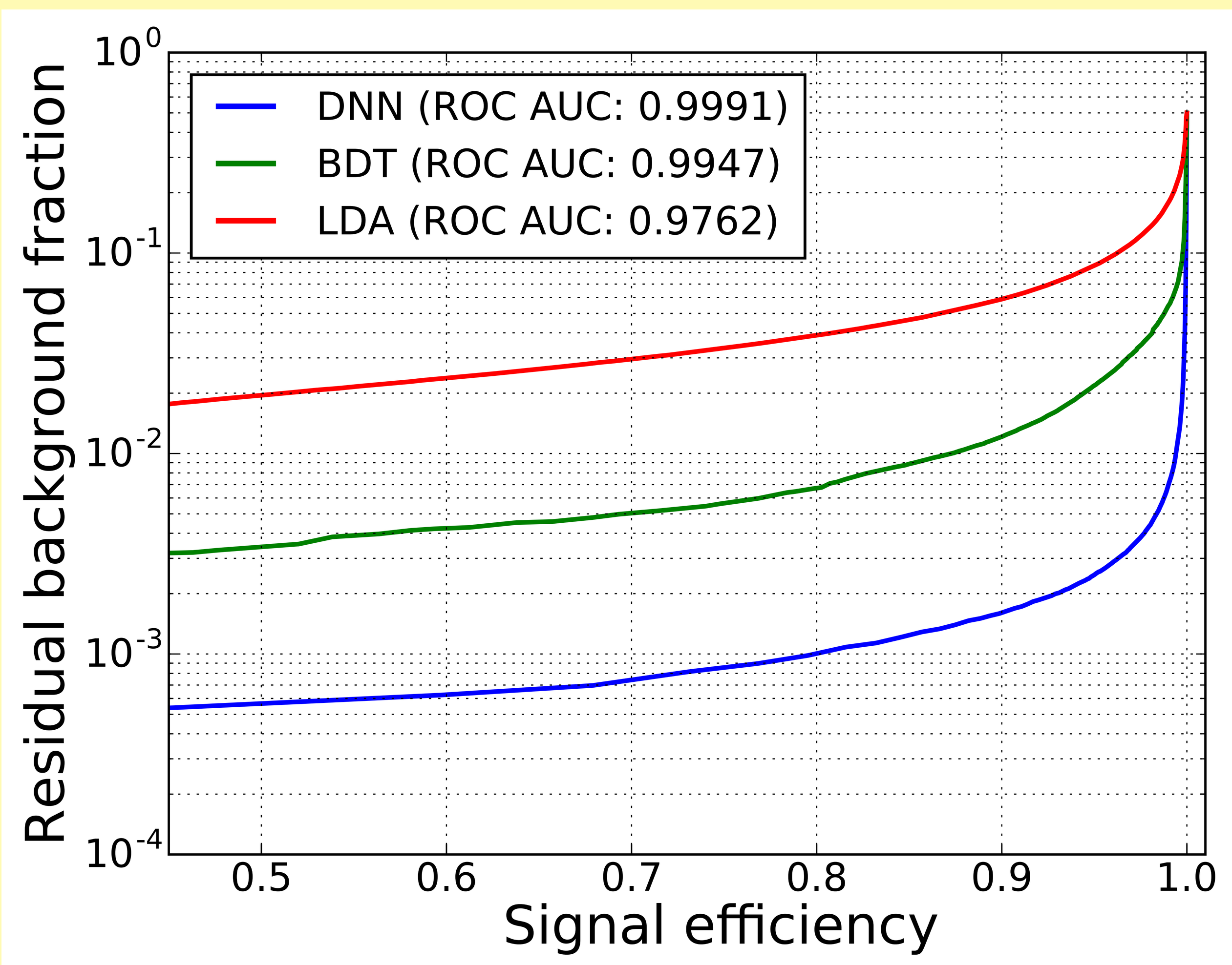
Classification



Evolution with number of variables



ROC curve



Conclusions & Limitations

- Deep Learning marginally outperforms gradient-boosted trees
- Fast running on GPU, with informations from many variables
- Can improve over cut-based analysis at high energies
- Non-trivial contamination in signal region, under investigation
- Trigger efficiency not taken into account

References
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- Goodfellow, I., et al. (2016) Deep Learning. MIT Press.

Software
- Keras: Chollet, F. & al. (2015). https://github.com/fchollet/keras
- Theano: Theano dev.team (2016) arXiv:1605.02688
- Scikit-Learn: Pedregosa, F., & al. (2011) J. of Machine Learning R.
- Nvidia CUDA: Nickolls,J. & al. (2008) Queue 6(2) 40-53