Tagging b jets Associated with Heavy Neutral MSSM Higgs Bosons

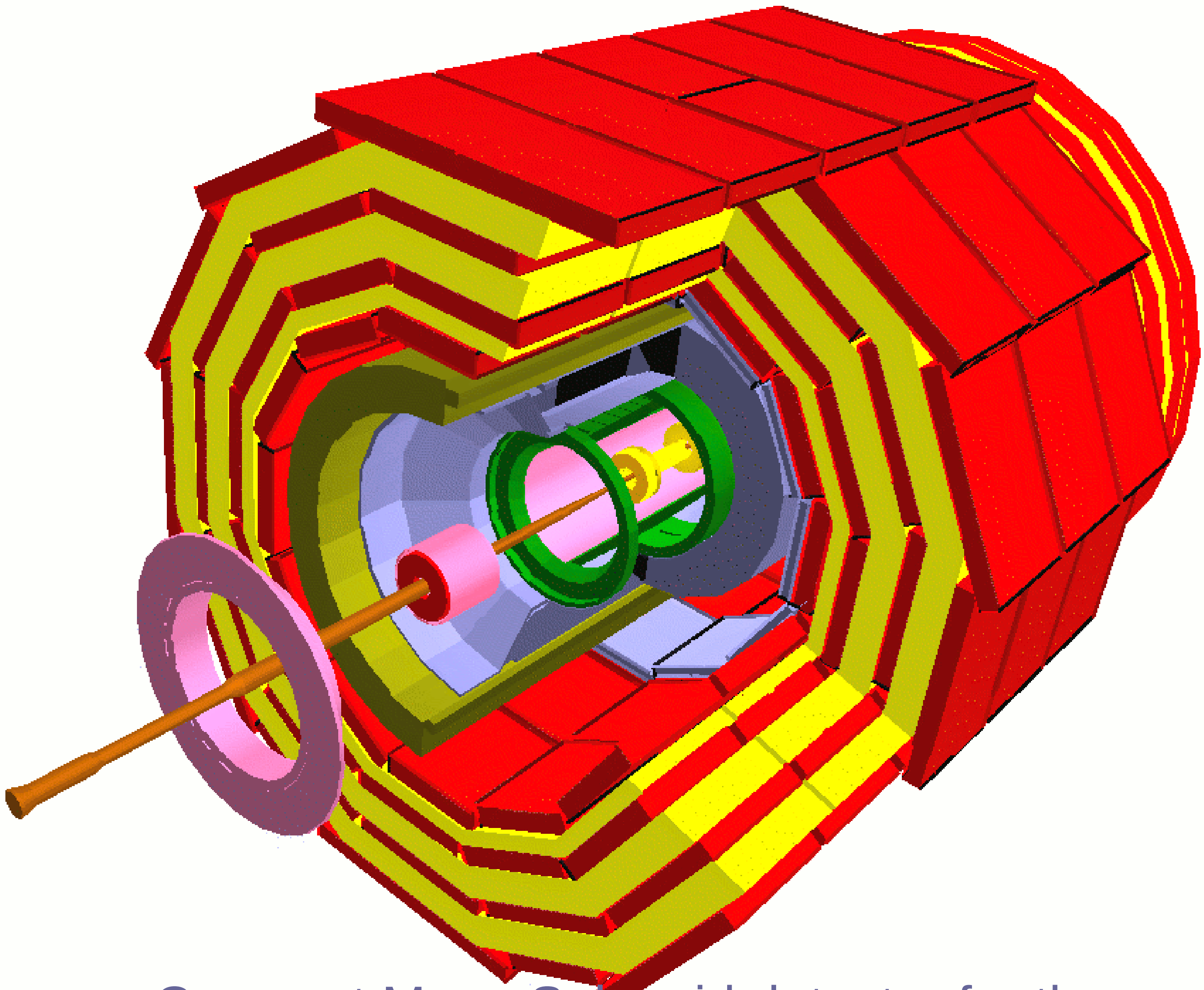
Aatos Heikkinen and Sami Lehti

HELSINKI INSTITUTE OF PHYSICS

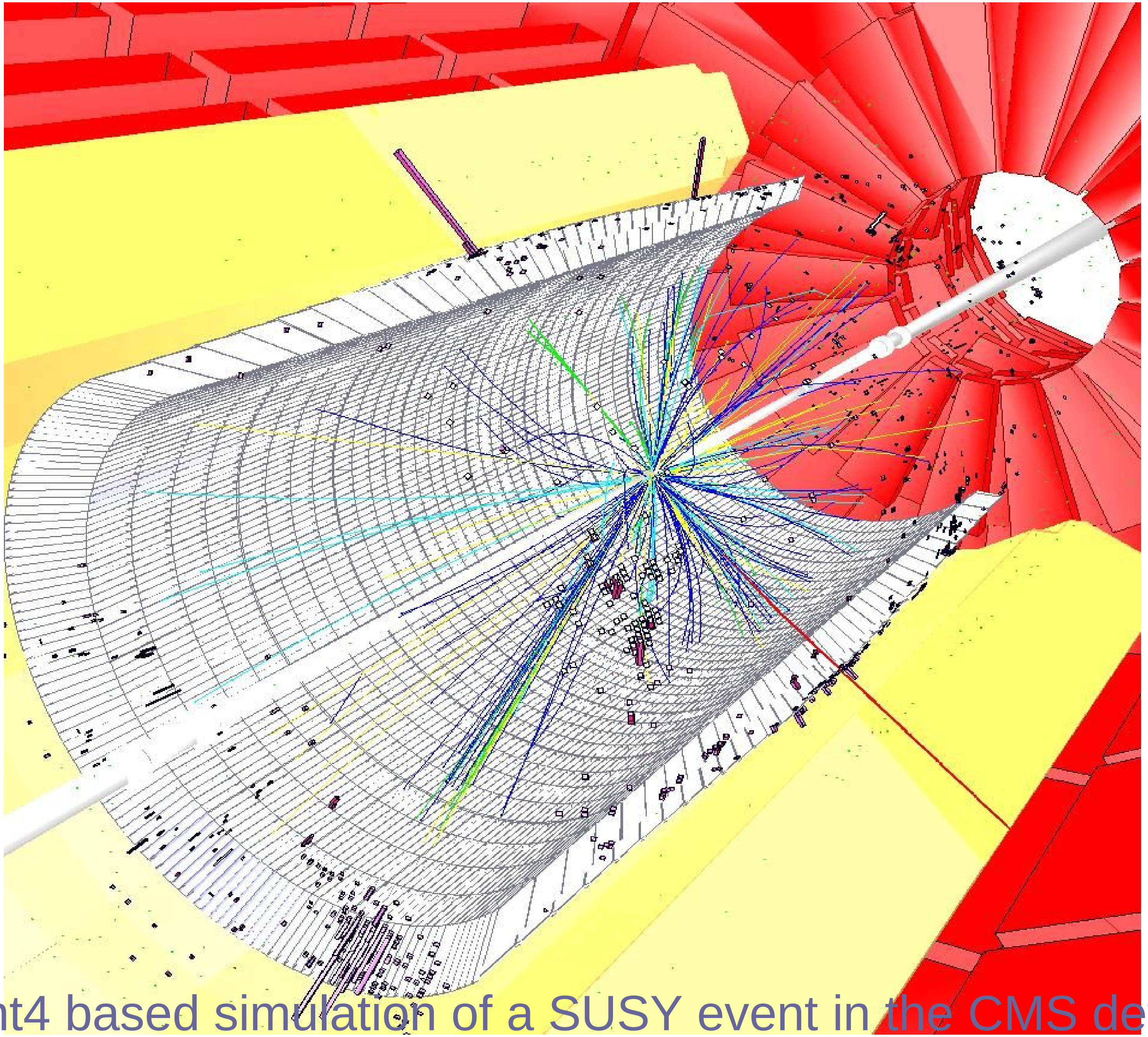
ACAT 2005
May 22 - 27, 2005
DESY, Zeuthen, Germany

Outline

- The problem of tagging b jets in the Compact Muon Solenoid experiment (CMS) at Large Hadron Collider (LHC)
  - Standard method of track counting
- Tools for the NN approach
  - ROOT tools
    - MLP and NeuNet
  - Kohonen's SOM and LVQ algorithms
    - SOM_PAK and LVQ_PAK
- Results from neural classification



Compact Muon Solenoid detector for the Large Hadron Collider.



Geant4 based simulation of a SUSY event in the CMS detector containing missing transverse energy, jets and several leptons in the barrel detector. *Picture: IguanaCMS.*

b-tagging

- At LHC the Higgs production in association with b-quarks

$$pp \to b\bar{b}H_{SUSY},\ H_{SUSY} \to \tau\tau$$

is the most important production mechanism for MSSM Higgs bosons at large tanβ

- The associated b-quarks hadronize forming soft jets, which can be used for identifying the signal events from the background

- b-tagging is a powerful tool to suppress the Drell-Yan background

$$pp \to Z,\gamma^* \to \tau\tau$$

for which the associated jets are mostly light quark and gluon jets, or which has no associated jets at all

Track counting b-tagging (1/2)

- The identification of b jets is based on the relatively long lifetime of B hadrons, $c\tau \sim O(5\ \mathrm{mm})$
  - Reconstruction of secondary vertex or
  - Measuring the track impact parameters (IPs)
    - Defined as the minimum distance between the track trajectory and the primary interaction point

Track counting b-tagging (2/2)

- The most simple algorithm to identify b jets is to count tracks in the jet cone with significant enough IP (IP/error)
  - This algorithm has been shown to give 35% tagging efficiency for b jets with 1% mistagging probability

- *S. Lehti, Tagging b-jets in $\rm b\bar{b}H_{SUSY} \rightarrow\tau\tau$, CMS NOTE-2001/019; G. Segneri and F. Palla, Lifetime Based b-tagging with CMS, CMS NOTE-2002/046.*

Neural network approach (1/2)

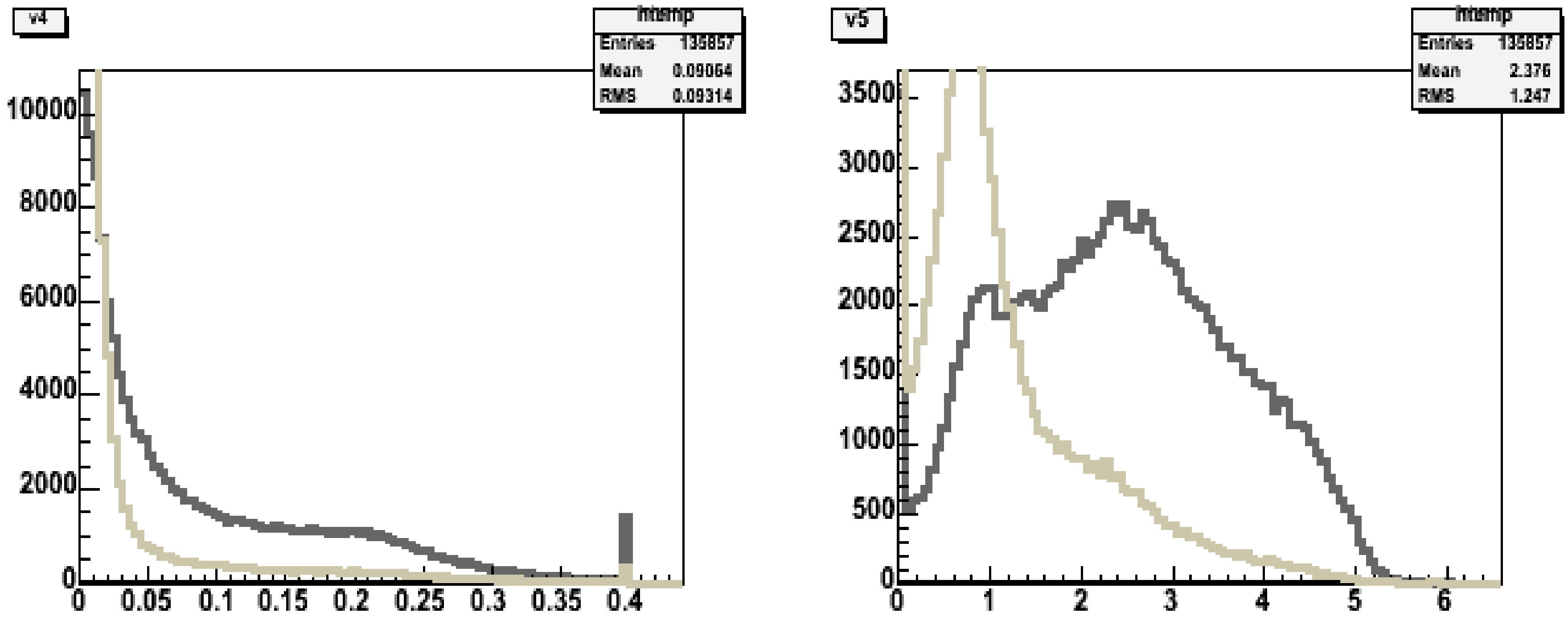
- Since a neural network (NN) approach has been shown to be applicable to the problem of Higgs boson detection at LHC, we study the use of NNs to the problem of tagging b jets

- *I. Iashvili and A. Kharchilava, $\rm H\rightarrow ZZ^*\rightarrow 4\ell$ Signal Separation Using a Neural Network, CMS TN-1996/100.*
- *M. Mjahed, Higgs search at LHC by neural networks, Nuclear Physics B 140 (2005) 799-801.*
- *F. Hakl et al., Application of neural networks to Higgs boson search, Nucl. Instr. & Meth. in Phys. Res. A 502 (2003) 489-491.*

Neural network approach (2/2)

- In the NN approach to the b-tagging problem we feed networks with the same events and the same seven variables as used in the traditional track counting algorithm
  - Number of tracks in the jet cone of 0.5
  - IPs and related IP significances for three leading tracks

- CMS ORCA simulation package (version 8_8_0) was used to create
  - 40k signal events
  - 40k Drell-Yan background events
  - Fully simulated with track and jet reconstruction



Example of variables used in the NN teaching. a) A leading track IP distribution for a signal and background events. b) A significance of a leading track IP.

Neural networks in data analysis framework ROOT (1/2)

- ROOT provides flexible object oriented implementation of MLPs
  - Various learning methods are provided
    - Steepest descent algorithm
    - Broyden-Fletcher-Goldfarb-Shanno algorithm
    - Variants of conjugate gradients
  - Visualization of the network architecture and learning process
  - Network can be exported as a standalone C++ code
- *ROOT - An Object Oriented Data Analysis Framework, Proceedings AIHENP'96 Workshop, Lausanne, Sep. 1996, Nucl. Inst. & Meth. in Phys. Res. A 389 (1997) 81-86.*

Neural networks in data analysis framework ROOT (2/2)

- ROOT provides also another feed forward NN tool NeuNet, which uses a common back-propagation learning method

- *J.P. Ernenwein, NeuNet, http://e.home.cern.ch/e/ernen/www/NN.*

Self-organizing maps

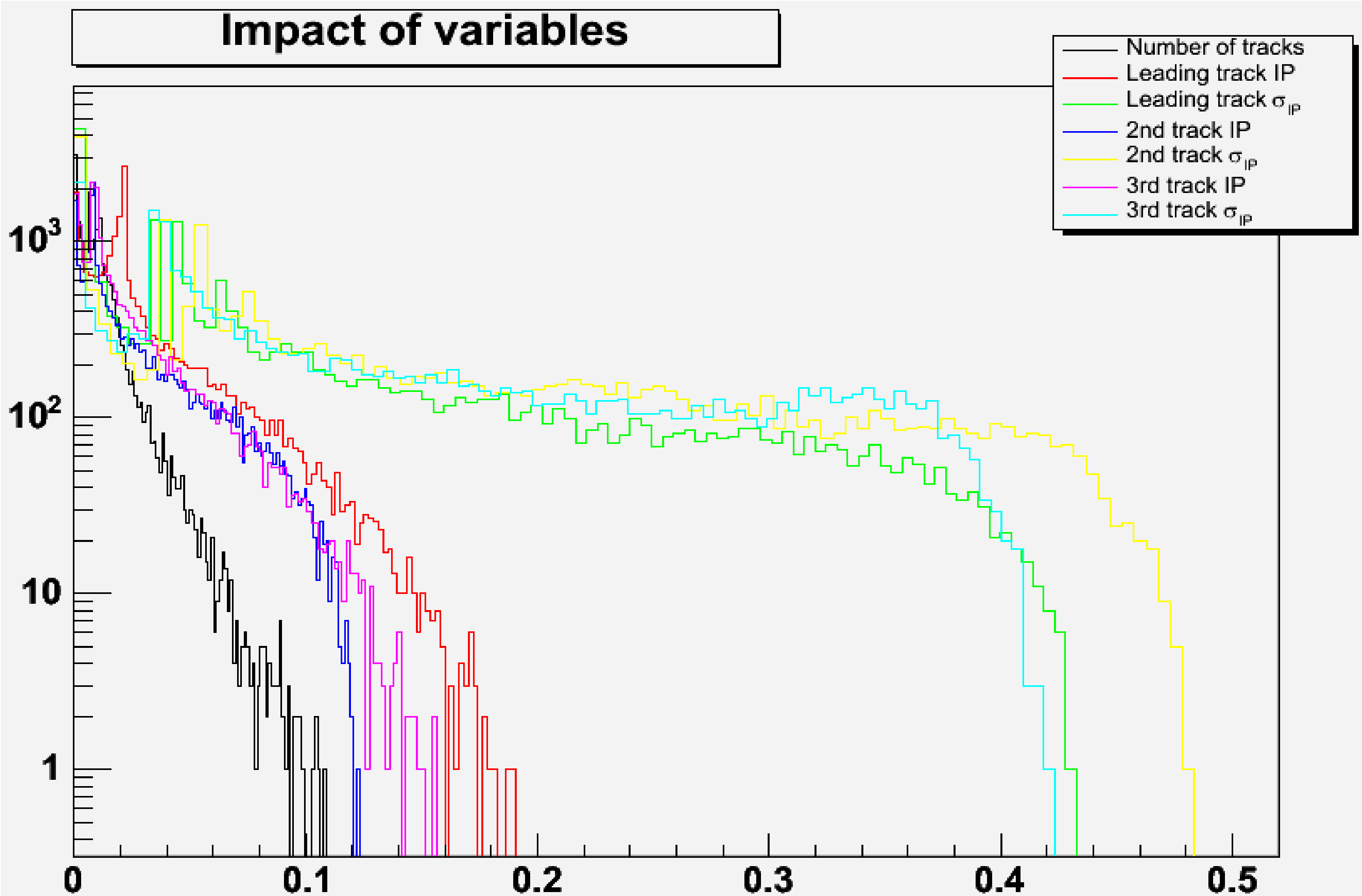
- We use public-domain program package SOM_PAK
  - C library from Helsinki University of Technology SOM programming team directed by Teuvo Kohonen
  - This unsupervised learning package provides compact implementation of SOM algorithm

- *http://www.cis.hut.fi/research/som-research/nnrc-programs.shtml*
- *T. Kohonen, Self-Organizing Maps, Springer-Verlag, Heidelberg, 1995.*

Learning vector quantization

- We use program package LVQ_PAK
  - C library from Helsinki University of Technology LVQ programming team
  - Implementation of the supervised Kohonen's LVQ algorithm is compact and fast

- *S. Haykin, Neural Networks, Prentice-Hall Inc, 1999.*

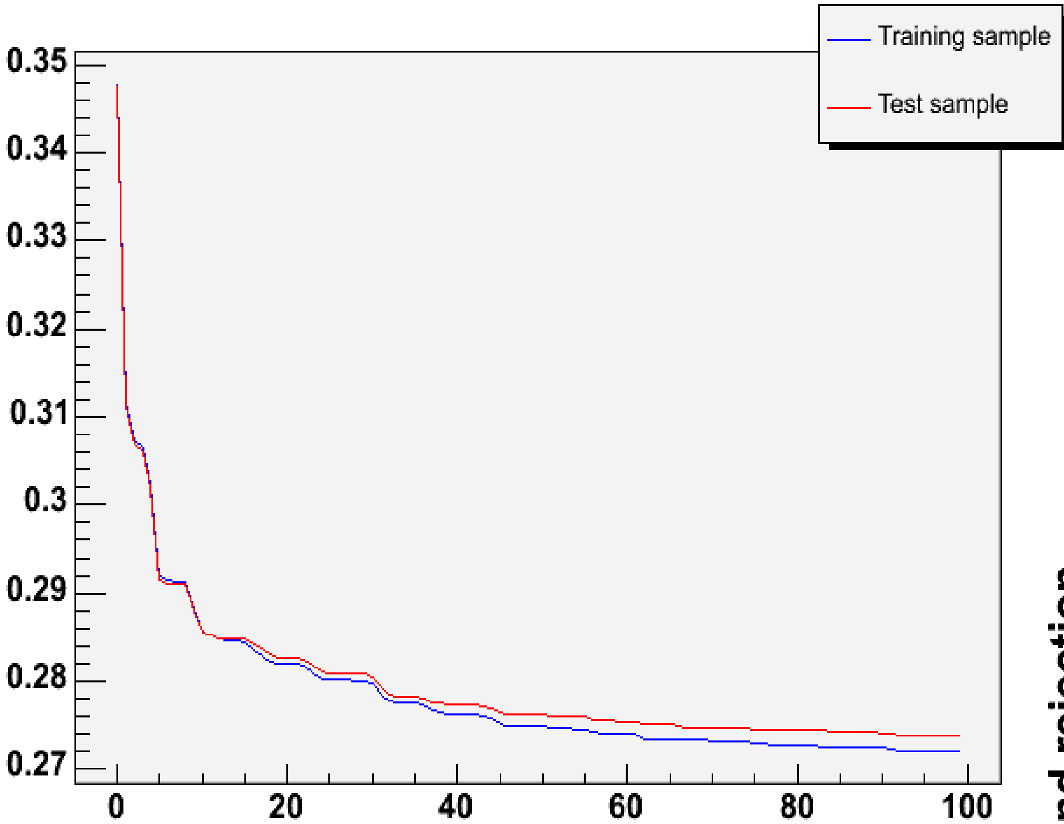


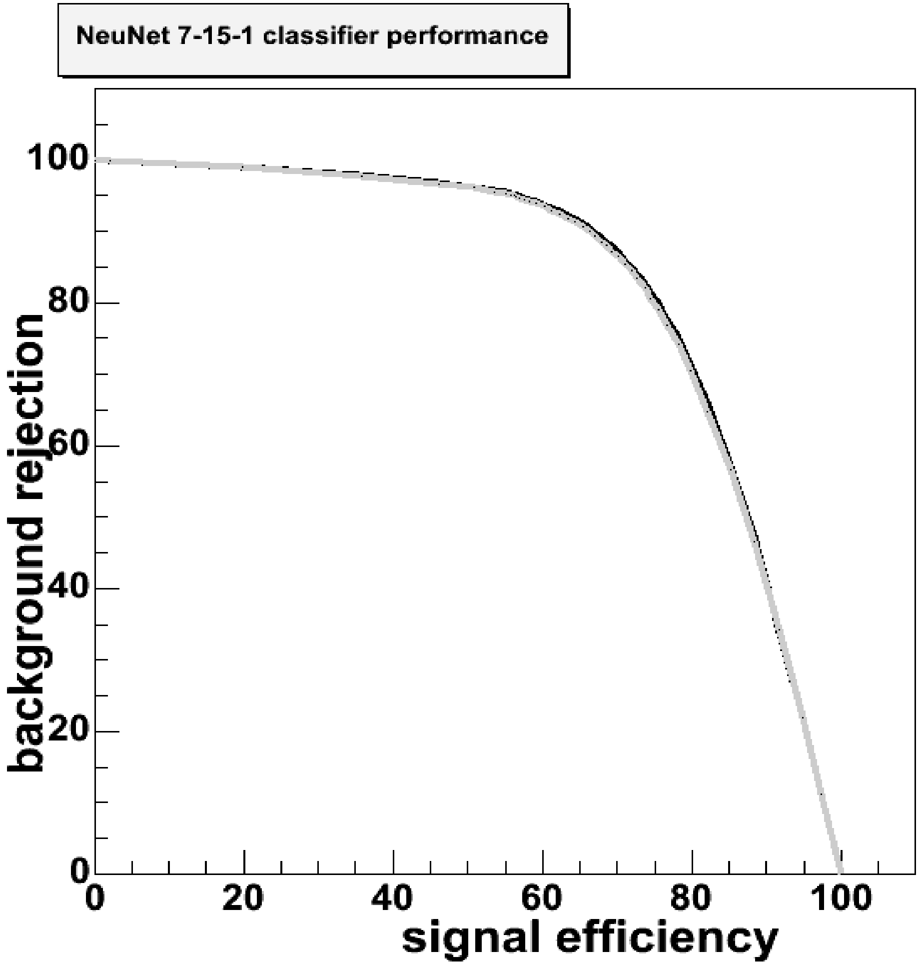
Example graphics from ROOT MLP tool. Impact parameter significances are found to have the best classification power.

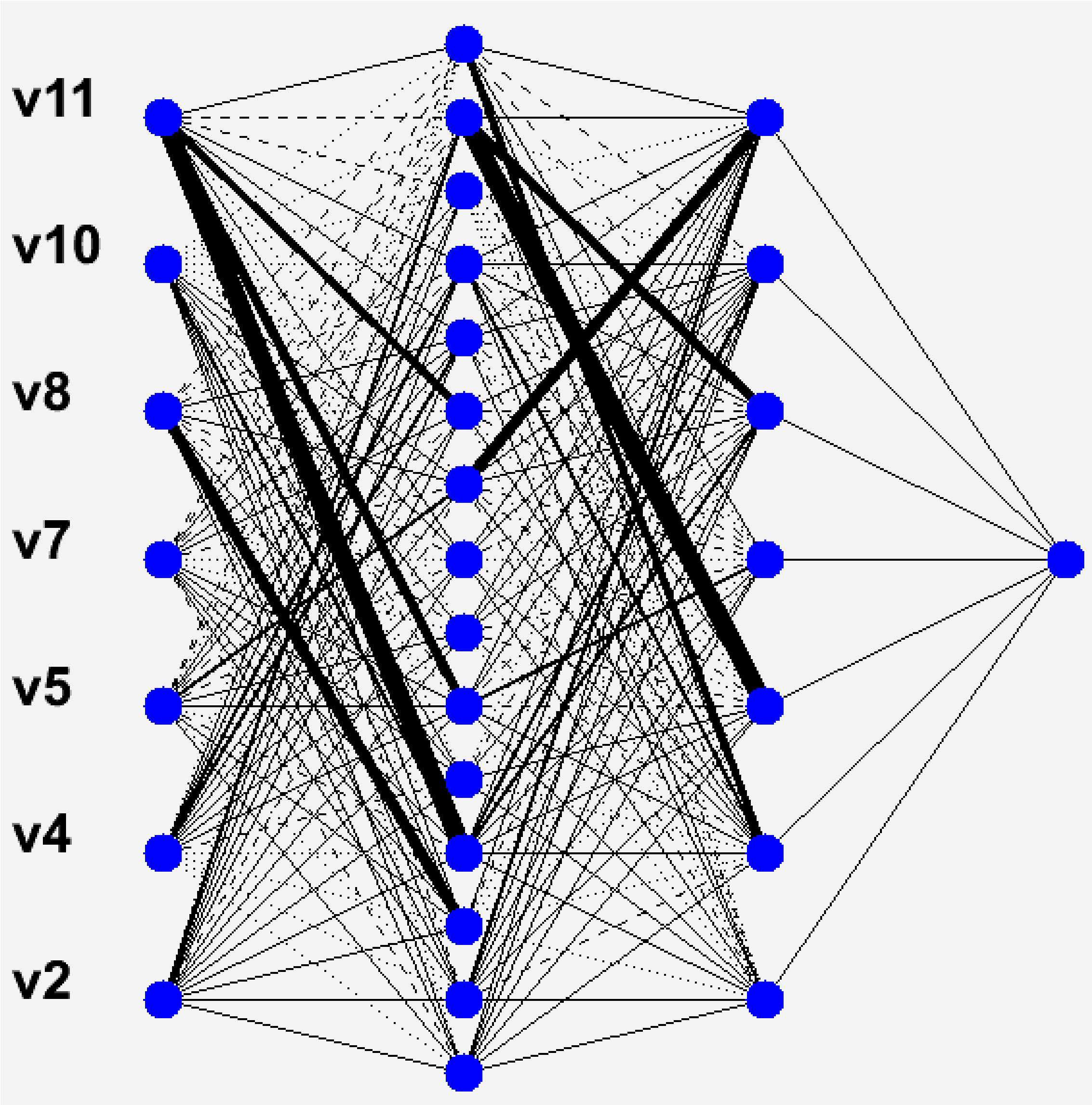
Choosing learning algorithm

- From different ROOT MLP learning algorithms we found Broyden-Fletcher-Goldfarb-Shanno algorithm (BFGS) best
  - Following results use this learning algorithm
- Also Stochastic minimization performed relatively well
  - This is the simplest learning method available in ROOT
  - Robbins-Monro stochastic approximation applied to MLPs
  - Further tuning of the parameters for this method might improve performance
- *C. Delaere, TMultiLayerPerceptron: Designing and using Multi-Layer Perceptrons with ROOT, http://www.fynu.ucl.ac.be/users/c.delaere/level2/MLP/.*

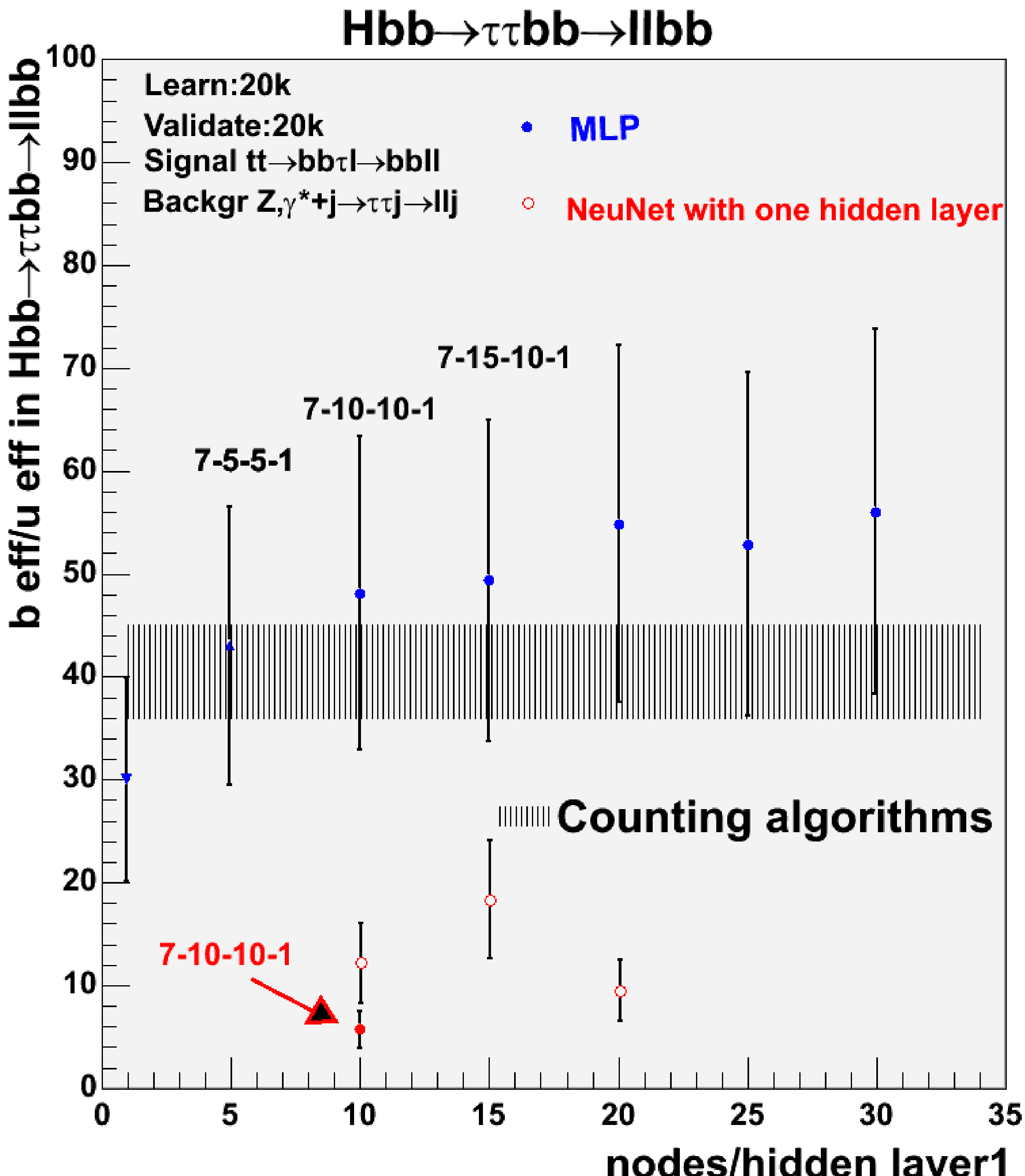
ROOT NeuNet and MLP Results





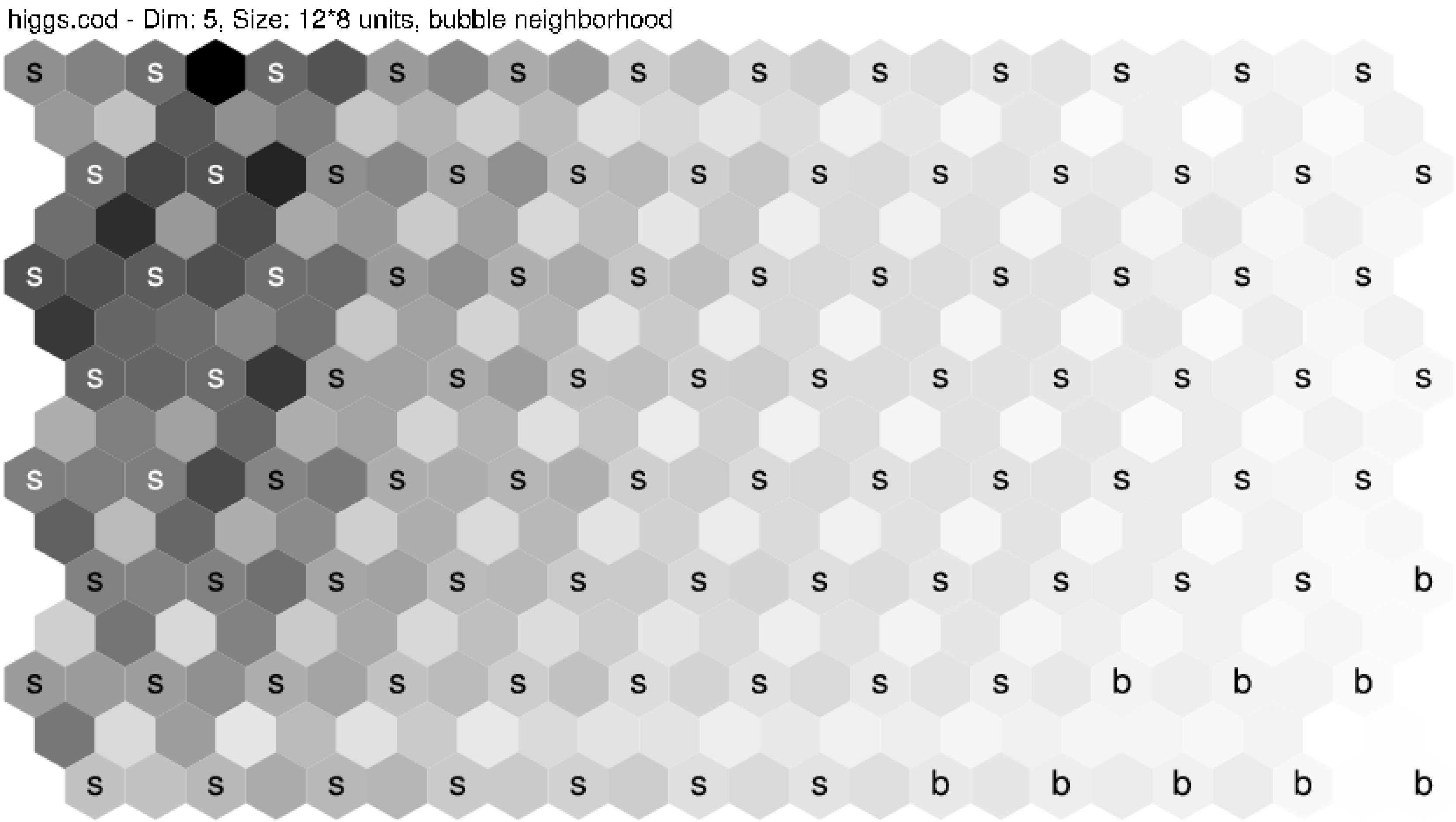


Example output from ROOT MLP tool. Neuron weights after learning in 7-15-7-1 configuration are shown.



Hbb→ττbb→llbb
Learn:20k
Validate:20k
Signal tt→bbτl→bbll
Backgr Z,γ*+j→ττj→llj
MLP
NeuNet with one hidden layer
7-5-5-1
7-10-10-1
7-15-10-1
Counting algorithms
7-10-10-1
b eff/u eff in Hbb→ττbb→llbb
nodes/hidden layer1
0
5
10
15
20
25
30
35
10
20
30
40
50
60
70
80
90
100

SOM and LVQ Results (1/2)



Example graphics from SOM_PAK. Semantic map after unsupervised learnig phase is divided into two regions representing signal (s) and background (b).

SOM and LVQ Results (2/2)

- Using same seven variables, SOM was able to classify unseen events with b-tagging efficiency of 72% with 12% mistagging rate
- SOM was able to filter away 44% of background events with 0.2% misclassification probability to signal
  - Further improvements are expected with SOM configuration optimization
  - Also, preliminary results on subsequent LVQ_PAK tuning indicate 2% tagging efficiency improvement

Conclusion

- We have shown that neural classification can be performed succesfully in b-tagging problems
  - ROOT tools MLP and NeuNet were found useful
- The classification power is competitive to traditional track counting method
- We have also shown how SOM can be teached to separate Higgs signal from LHC background
- Simultaneous use of traditional tagging methods and neural computing, including unsupervised teaching, is promising technique for Higgs particle searches