



# Machine Learned Tracklet Filters - Update

## Rudolf Früwirth, Jakob Lettenbichler, Thomas Madlener



02.09.2015



- 王



Rudolf Früwirth, Jakob Lettenbichler, Thomas Madlener



Global Resu

Detailed Results



#### What happened since Vienna?

Wrap up

- Development of tools for testing feasibility of incorporating advanced machine learning (ML) approaches into SectorMap approach of VXDTF
- Testing of different ML classifiers
  - Multilayer Perceptron
  - Boosted Decision Trees
- Started writing of Thesis





Replace/Support three hit filters with a ML classifier

- use three hit combinations passing the two filter stage of the VXDTF as inputs
  - ightarrow SNR pprox 0.75 after two hit filters
- ML classifier labels input as signal or background

Possible Advantages:

- + Better separation of signal and background compared to current approach
  - $\rightarrow$  Reduced combinatorics in later stages
- + Generalization capabilities require reduced amount of
  - training samples
  - sectors / SectorMaps



Global Results

Detailed Results



## **ML Classifiers**

# Tested classifiers:

Multilayer Perceptron (MLP)

- one hidden layer with different numbers of neurons
- different activation functions of output neuron:
  - logsig: logistic function  $f(z) = (1 e^{-t})^{-1}$
  - linear: linear function f(z) = z
- o done with MATLAB

Boosted Decision Trees (BDT)

- different Boosting algorithms:
  - AdaBoost (MATLAB)
  - Stochastic Gradient Boosting (FastBDT, BASF2)
- different tree depths / numbers of decision splits
- different numbers of boosting steps



프 🖌 🖌 프





### **Generation of Training and Test Samples**

Plan:

- use SegmentNetwork to get samples/inputs
- feed tracklets from SegmentNetwork to classifier → classifier is a 'pluggable' substitute to current filters
- in a first step use SVD only

But:

- not yet ready in framework
- 'misuse' current VXDTF to generate samples

*classifier* - machine learned instance (BDT, MLP) with output that makes classification into background/noise and signal possible





Global Resu

Detailed Results



#### Generating Samples with current VXDTF

Wrap up

- simulate generic events with background
- VXDTF to get track candidates:
  - enable only two hit filters
    - distance3D
    - o distanceXY
  - disable filtering/cleaning of overlapping track candidates (i.e. disable Hopfield network or greedy algorithm)
  - tune CutOff Values by 6 % (tuneCutOffs: 0.06)
- convert to SPTCs for further processing
  - disable usage of single Cluster SPs (need global position)
- create three hit samples from SPTCs
  - split SPTC into tracklets containing three SpacePoints each



→ E > < E</p>



- hits are on consecutive layers (i.e. no overlapping parts at the moment)
- if all SpacePoints have relation to the same MCParticle  $\rightarrow$  signal sample, else background/noise sample
- relations to other MCParticles are not considered
- SpacePoints with no relation to any MCParticle  $\rightarrow$  background/noise sample

Input of classifiers:

global coordinates of SpacePoints  $\rightarrow \boldsymbol{x} \in \mathbb{R}^9$ 



> < ≣





background/noise sample:



★ Ξ > ★ Ξ >



The whole data set is split up in a training set and a testing set (not used in training at all)

- For comparable results the same training and testing sets are used for all classifiers.
- Still some randomness in training (network initialization, random splits in stochastic gradient boosting)
- Input data is decorrelated before splitting (negligible difference)
- Comparison of output distributions of both sets used to check if a classifier is overtrained



★ E → < E</p>



Global Results

Detailed Result

Summary & Outloc



#### **Determining Classification Cut**





efficiency and SNR in output (SNR<sub>out</sub>) depending on the applied classification cut

SNR<sub>out</sub> - ratio of true positives to false positives



ъ



Detailed Results

## OAW

#### **Comparison of different classifiers**



SNR gain vs. efficiency for different tested classifiers

SNR gain = SNR<sub>out</sub>/SNR<sub>in</sub>

Classifiers:

- MLP logsig 50 hidden neurons, logsig output
- MLP linear 50 hidden neurons, linear output
- **BDT** 50 decision splits, 2000 boosting steps, *AdaBoost*
- FastBDT tree depth 6, 2000 boosting steps





**Global Results** 

Detailed Results



#### **Comparison of different classifiers**

- $\rightarrow$  Decorrelating improves performance of all tested classifiers by a factor of approx. 1.3 1.6
- → BDTs (including FastBDTs) generally perform better than MLPs (at least with 50 hidden neurons)
- → evaluation time rules out BDTs trained with AdaBoost (table below)

[µs/sample]	training	evaluation
MLP w/ <i>H</i> = 50	$\sim 2400-3400$	$\sim 2.1-2.4$
BDT w/ <i>D</i> = 50, <i>N</i> = 2000	$\sim 10^4$	$\sim 10^3$
FastBDT w/ <i>N</i> = 2000	$\sim 250-270$	$\sim 10 - 10^{2}$

NOTE: MLP tested with MATLAB  $\rightarrow$  evaluation times probably do not translate to BASF2



▶ < Ξ





#### Performance Analysis

Perform a more detailed analysis of the classifiers to spot possible weak (or sweet) spots

- $\theta$  and  $\phi$ -dependent performance
- p- and  $p_T$ -dependent performance
- charge and PDG code dependent performance





Prerequisites for following analysis:

- Only one (global) classification cut determined from overall performance, such that overall efficiency is  $\geq$  0.99
- No MC information available for background samples
  → only efficiency can be analyzed

Main Result:

- $\rightarrow\,$  all tested classifiers show qualitatively same characteristics
- $\rightarrow$  following plots obtained with best performing FastBDT (tree depth = 6, 2000 boosting steps)



프 🖌 🖌 프



**Global Results** 

Detailed Results



#### $\theta$ -dependent performance







> < ≣

Rudolf Früwirth, Jakob Lettenbichler, Thomas Madlener



**Global Results** 

Detailed Results



#### $\theta$ -dependent performance



SNR in input and output and ratio in bins of  $\theta$ 



efficiency in bins of  $\theta$ 



ъ



- $\rightarrow\,$  Efficiency stable over wide range, dropping below 0.99 at the edges only
- $\rightarrow$  Efficiency below 0.9 only at  $\theta$  outside of official detector boundaries
- $\rightarrow\,$  SNR gain stable at approx. 3 4 for wide range reaching up to almost 30 for forward direction with high background
- $\rightarrow\,$  choosing cuts such that each bin has 0.99 efficiency yields similar results with reduced SNR gain at the edges





**Global Results** 

Detailed Results



#### phi-dependent performance





ъ

Rudolf Früwirth, Jakob Lettenbichler, Thomas Madlener



**Global Results** 

Detailed Results



#### $\phi$ -dependent performance



SNR in input and output and ratio in bins of  $\phi$ 





ъ



Global F

Detailed Results



#### $\phi$ -dependent performance

- ightarrow Efficiency stable  $\ge$  0.98 over whole range
- $\rightarrow \text{ SNR}_{\text{out}}$  stable over whole range
- $\rightarrow\,$  SNR gain with broad peak around  $\phi\approx$  40 due to high background in input there
  - $\rightarrow$  unclear if this is due to SectorMap or stems from simulation
  - → naively expected an almost flat distribution as input
- $ightarrow \,$  dips in output at overlapping parts of layer 4
  - $\rightarrow$  hits in overlapping parts excluded
  - $\rightarrow$  Why from layer 4?
- $\rightarrow\,$  choosing cuts such that efficiency is 0.99 in all bins has no significant effects



→ E > < E</p>



o up

Global Results

Detailed Results

Summary & Outloo

OAW

# p- and $p_T$ -dependent performance



- ightarrow efficiency  $\geq$  0.95 for all values of p and  $p_T$
- ightarrow only first bin ( $p_T = 0.1 \, \text{GeV/c}, \, p = 0.12 \, \text{GeV/c}$ ) below 0.99 efficiency





/rap up

**Global Results** 

**Detailed Results** 

Summary & Outloo



# charge and PDG code dependent performance





 $\rightarrow\,$  Efficiency higher for neg. charged particles although number of pos. and neg. charged particles almost balanced

- ightarrow Effect is bigger for decorrelated data
- ightarrow lowest efficiency for  $e^-/e^+$





## Summary

- $\rightarrow\,$  BDTs (incl. FastBDTs) with better classification performance compared to MLPs
- $\rightarrow\,$  **Decorrelation** of inputs improves performance of all tested classifiers significantly
- $\rightarrow\,$  Performance looks promising however no real prediction possible on the impact on the VXDTF

# **Open Question**

- $\rightarrow$  Why is input not flat in  $\phi$ ?
- $\rightarrow$  Why is efficiency better for neg. charged particles?
- → How does this effect the VXDTF?

Summary & Outlook

★ E → ★ E →



# **Next Steps**

- $\rightarrow$  Check input distribution in  $\phi$  with particle gun instead of generic events and without background to discern 'external' sources
- $\rightarrow\,$  Check performance in cases where hits are not on consecutive layers
- $\rightarrow\,$  Once SectorMap is ready check how ML filter can be implemented and test effects
- $\rightarrow$  Continue writing theses
- $\rightarrow$  ... Your Suggestions / Requests

∃ → < ∃ →</p>

Summary & Outlook

Y v

**Global Results** 

Detailed Result



# Thank You

# **Questions or Remarks?**



Rudolf Früwirth, Jakob Lettenbichler, Thomas Madlener