Machine Learning Assisted Track Finding in the Belle II SVD

Thomas Madlener
for the Belle II Tracking group

HEPHY Institute of High Energy Physics

Connecting the Dots 2016 - Vienna

ÖAW Austrian Academy of Sciences

23.02.2016

Some Information on Belle II

... can be found in talks given by

- Sebastian Skambraks: *The NeuroZ-Vertex Trigger of the Belle II Experiment*
- Oliver Frost: *Tracking in the Belle II Drift Chamber*
- Jakob Lettenbichler: *Tracking in the Belle II Vertex Detector*

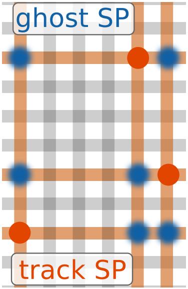
Challenges and Short Recap of SectorMap

Goal:

low momentum track finding down to $p_T \approx 50\,\mathrm{MeV}/c$

Main Challenges:

- Energy loss and multiple scattering influence particle trajectory
- Limited reconstruction time
- Ghost SpacePoints on strip detectors



SectorMap:[a]

- divide detector into small sectors
- use relations between sectors to define cut-off filters for hit combinations

[a] see talk by Jakob Lettenbichler

Bringing Machine Learning into play

Advantages and Challenges of the SectorMap:

- \+ Fast filtering with high efficiency
- – Tuning of a large number of filters and sector relations
- – Training very resource demanding

Hopes in Supervised Machine Learning:

- \+ Exploit generalization capabilities
  - \+ Less sectors required
  - \+ Less training data required
- \+ Improved signal and background separation
  - \+ Higher coverage of input space

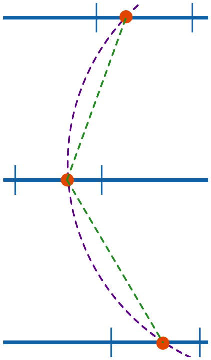
? Is it possible to exchange a large number of simple filters by a small number of ML filters ?

The Approach and Training

Incorporate Machine Learning into SectorMap:
2-SpacePoint combinations processed by standard filters

Use a Boosted Decision Tree (BDT) to filter 3-SpacePoint combinations:

- inputs: $x \in \mathbb{R}^9$ - (3×3) spatial coordinates of SpacePoints
- outputs: $y \in \mathbb{R}$ - use cut to decide signal/background
- label: from full detector simulation
  - $\rightarrow$ signal if all SpacePoints from same MC particle



Some words on the simulation

Simulation setup:

- limited θ-range: $60^\circ \leq \theta \leq 85^\circ$
- particle gun: 10 μ tracks per event
- low momentum range: $100\,\mathrm{MeV/c} \leq p_T \leq 145\,\mathrm{MeV/c}$
- no additional background

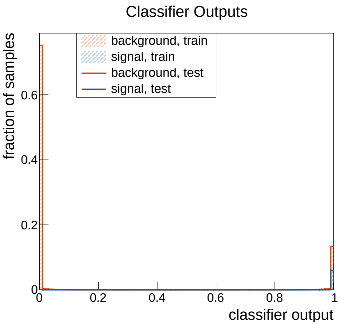
Results in:

- track hits / ghost hits ≈ 0.5
- signal / background ration in input ≈ 0.08

Expected in experiment:

- $\Upsilon(4S)$-events: on average $\approx$ 10 tracks per event
- signal / background in input $\approx$ 0.1 (incl. machine bg)

Classifier Performance

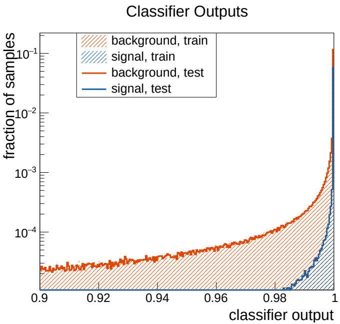


- good clustering of signal samples
- cut is defined to reach 99 % signal efficiency
- majority of background rejected

	cut	bg. reject.
train	0.906	81.53 %
test	0.912	81.68 %

$\rightarrow$ training a classifier for the purpose is possible

Classifier Performance



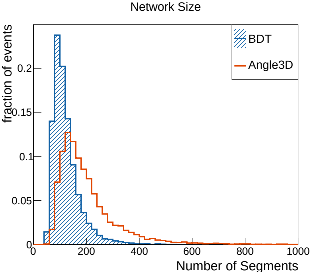
- good clustering of signal samples
- cut is defined to reach 99 % signal efficiency
- majority of background rejected

	cut	bg. reject.
train	0.906	81.53 %
test	0.912	81.68 %

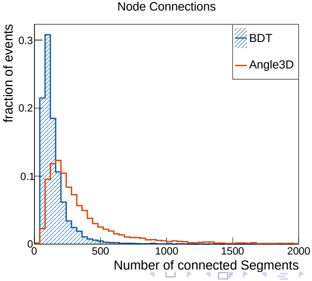
$\rightarrow$ training a classifier for the purpose is possible

Comparison with Angle3D filter

Both approaches used same events (for training and for testing)



- Network size is indicator for bg rejection
- Smaller networks processed faster by Cellular Automaton
- BDT yields smaller Networks
- Angle3D and BDT with $\approx 99\,\%$ efficiency after Cellular Automaton
- Clone and ghost/fake rate lower by factor $\approx 3-4$ for BDT



Conclusion & Outlook

Conclusions:

- Machine Learned Filter with promising results
- Tests not done on full detector and momentum range
  - → Standard filters not affected
  - → ML filters could degrade significantly

Outlook and ToDo's:

- Test on full detector and momentum range
- Test with physics simulation data
- Compare execution time
- Test feasibility of different ML classifiers for different detector regions

Suggestions:

- Any other thoughts or ideas from YOUR side?

Backup