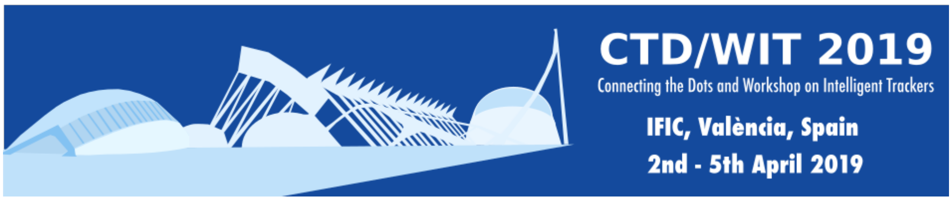


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# Machine Learning For Track Finding

*Wednesday, April 3, 2019 12:00 PM (25 minutes)*

The $\bar{\mathrm{P}}$ANDA (anti$\bar{\mathrm{P}}$roton ANnihilation at Drmstadt) experiment at the future Facility for Antiproton and Ion Research (FAIR) in Darmstadt, Germany, will investigate the behavior of QCD in the mass range of the charmonium. As a fixed target experiment, most of the generated particle will have a forward boost. Therefore, the PANDA detector consists of a Central Spectrometer (CS), directly around the interaction point and a Forward Spectrometer (FS) measuring the forward going particles. The FS is located downstream of the interaction region and measures particles at small polar angles $\theta$ below $5^\circ$ in the vertical and $10^\circ$ in the horizontal plane. Its magnetic field with a maximum bending power of 2 Tm is provided by a dipole magnet. For the measurement of particle momenta based on the deflection of their trajectories in the magnetic field of the FS dipole magnet, Forward Tracker Stations (FTS) are foreseen. The design of the FTS is based on self-supporting straw tubes arranged in three pairs of planar stations. One pair (FT1, FT2) is placed upstream of the FS dipole magnet, the second pair (FT5, FT6) downstream of the magnet, and the third pair (FT3, FT4) is placed inside the gap of the magnet. Each tracking station consists of four double layers of straws: the first and the fourth one are vertical straws and the two intermediate are composed of straws tilted at $+5^\circ$ and $-5^\circ$, respectively.

We apply machine/deep learning methods as a track finding algorithm at the FTS.
The problem is divided into two steps:

The first step is to build track segments in three different parts of the FTS, namely FT1, FT2, and FT3. Two models were tested in this step so far, the first model relies on unsupervised clustering algorithm to find track segments, and the second model relies on supervised learning to combine hit pairs/triplets to form track segments in the three different parts of the FTS.

The second step is to join the track segments from the different parts of the FTS to form a full track, and is based on Recurrent Neural Network (RNN). The RNN is used as a binary classifier that outputs 1 if the combined track segments are a true track, and 0 if the track segments do not match. The performance of the algorithm is judged based on the purity, efficiency and the ghost ratio of the reconstructed tracks. The purity specifies which fraction of hits in one track come from the correct particle. The correct particle is the particle, which produces the large majority of hits in the track. The efficiency is defined as the ratio of the number of correctly reconstructed tracks to all generated tracks present. The ghost ratio is defined as the number of impure tracks (which have a large fraction of hits from more than one track) to all tracks present.

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**Track Classification:** 1: Machine learning, algorithms and theoretical analysis