Studying the Tracking Resolution of the MUSE Straw Tube Trackers

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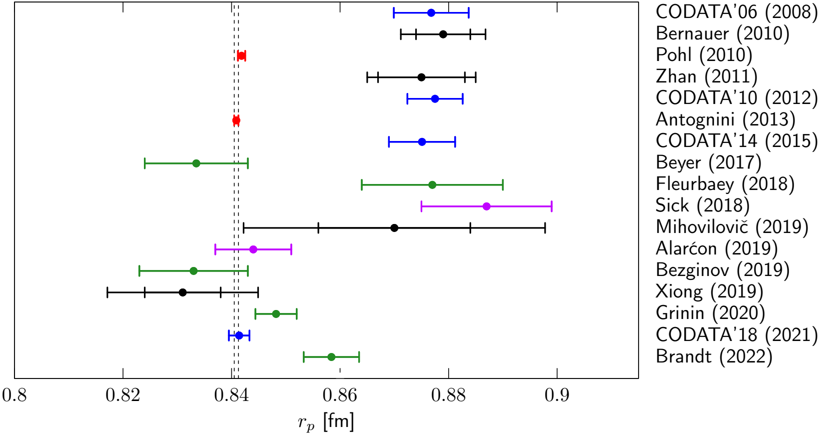
The MUon Scattering Experiment (MUSE)

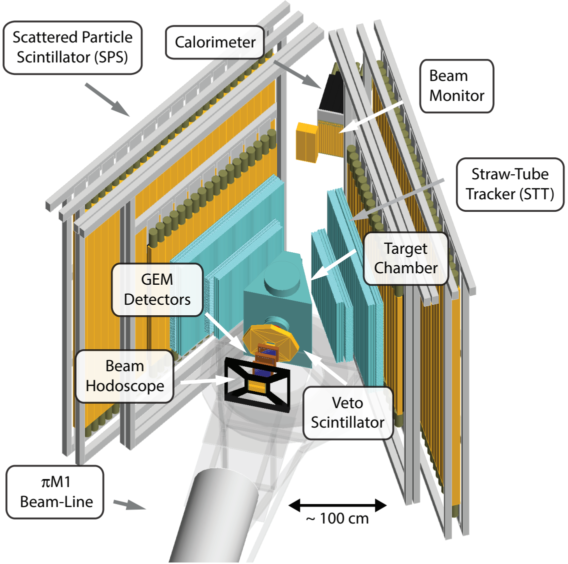
- 2010: CREMA extract r_p through muonic hydrogen spectroscopy
  - $\sim 7.9\sigma$ from average ep scattering value at time
- Birth of Proton Radius Puzzle



MUSE

- The MUon Scattering Experiment (MUSE) was directly inspired by the proton radius puzzle
- Goals:
  - Precision measurement of r_p via ep and μp scattering
  - Precision study of TPE in ep and μp scattering
  - Direct test of lepton universality
- Housed at the πM1 beamline at the Paul Scherrer Institute

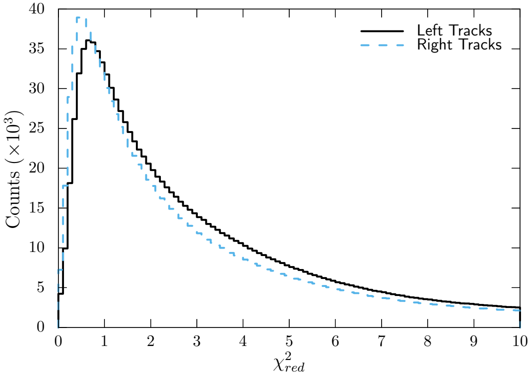
- θ acceptance: $20 - 100^\circ$
- $\pi M1$ Beam Line:
  - p$\in 115, 160, 210$ MeV/c
  - Mixed beam of e, μ, π
  - Both polarities of particles!

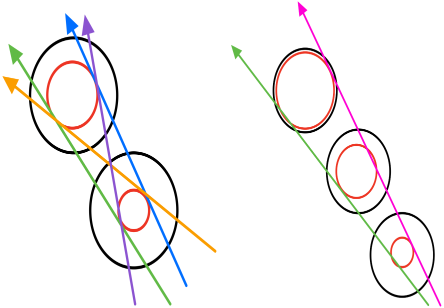


The Straw Tube Trackers (STT)

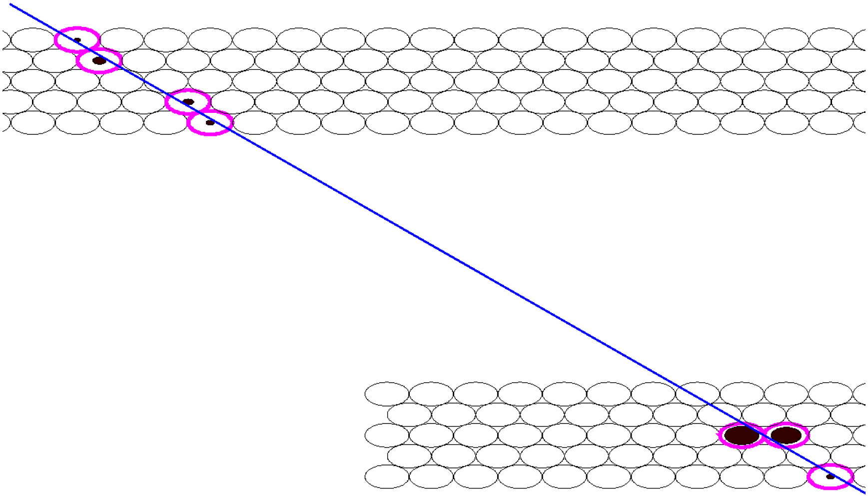
- Primary scattered particle tracking detector in MUSE
- Mirrored setup:
  - 20 planes of straws (10 horizontal, 10 vertical)
    - Vertical planes: θ
    - Horizontal planes: ϕ
  - Smaller front chamber, larger rear chamber
  - 5.1mm straw radius, 60 and 90 cm long
  - $\sim$ 3000 straws total

- Process:
  - Filter out noise hits/group tracks together
  - Parametrize track using spherical coordinates → 4 free parameters
  - Minimize χ^2 of track to hits (represented by cylinders)
  - Difficulty: "Left-Right Ambiguity"

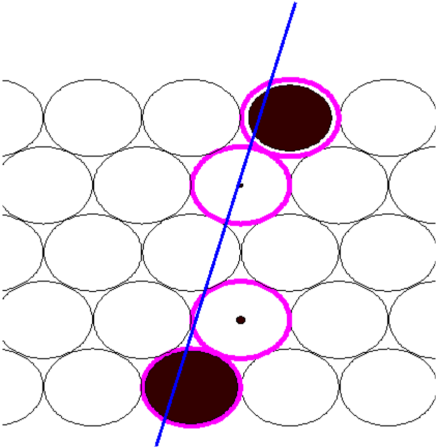




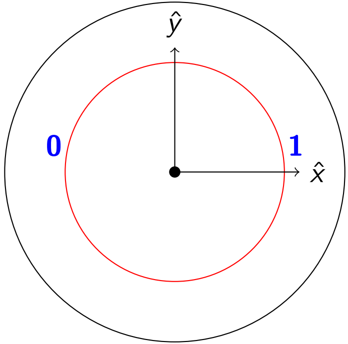
STT Tracking: Sample Event



STT Tracking: Sample Failure Event



- As discussed last time: ML possibly can be used to assist
- Idea of NN:
  - Work in local frame of straw (top down view)
  - Find which "side" simulated track passes on
  - Output: binary left/right ($y \approx 0$ more often than not)

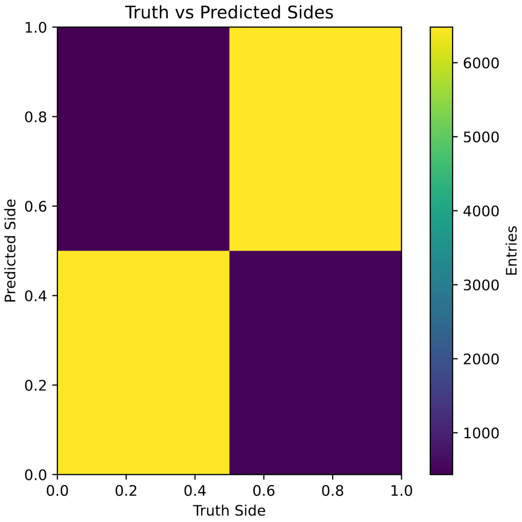


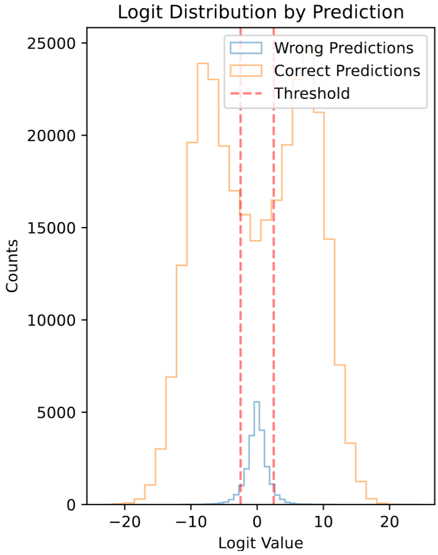
NN Structure

- Shallow network, bias=False because of batch norms
- Input: $(BATCH, 2, 10, 89)$ (binary 0/1 hit per straw, then the fired radii)
- Output: logit (strength of prediction and side) for each straw
- Loss function: BCEWithLogitsLoss (masked to only fired straws)

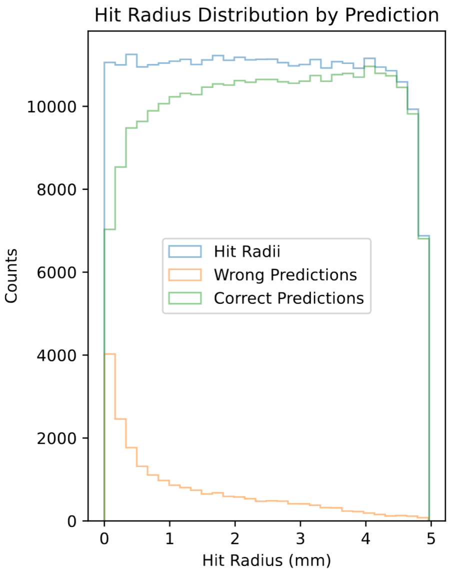
```python
self.sequence = nn.Sequential(
    nn.Conv2d(2, 8, kernel_size=(10,4), padding=(5,2), bias=False), # 0
    nn.BatchNorm2d(8), # 1
    nn.ReLU(inplace=True), # 2
    nn.Dropout2d(0.075), # 3

    nn.Conv2d(8, 16, kernel_size=(5,4), padding=(2,2), bias=False), # 4
    nn.BatchNorm2d(16), # 5
    nn.ReLU(inplace=True), # 6
    nn.Dropout2d(0.075), # 7

    nn.Conv2d(16, 1, kernel_size=2), # 8
    nn.ReLU(inplace=True), # 9
    nn.Dropout2d(0.075), # 10

    nn.Flatten(), # 11
    nn.Linear(900, 256, bias=False), # 12
    nn.ReLU(inplace=True), # 13
    nn.BatchNorm1d(256), # 14

    nn.Linear(256, input_size) # 15
)
```

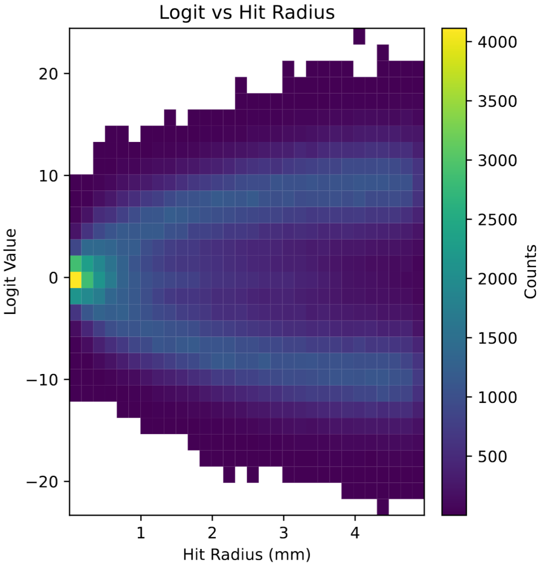
Results: Correlation and Logits





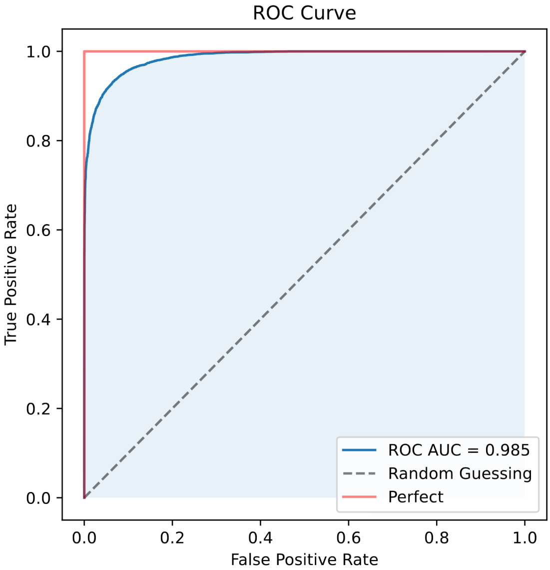
Hit Radii vs Correctness





Model Behavior

- Measure of performance: Receiver Operating Characteristic (ROC) Curve
  - Used primarily in medical diagnostics
  - Graphical way to gauge binary classifier performance
  - Higher area under curve (AUC) is better
- AUC of 0.985 - incredibly strong model at predicting left/right
- Cut on: $|\text{logit}| \geq 2.5$ and $r_{\text{drift}} \geq 1mm$ radii: 99.4% LR correct on validation set!



Implementation in Trackers

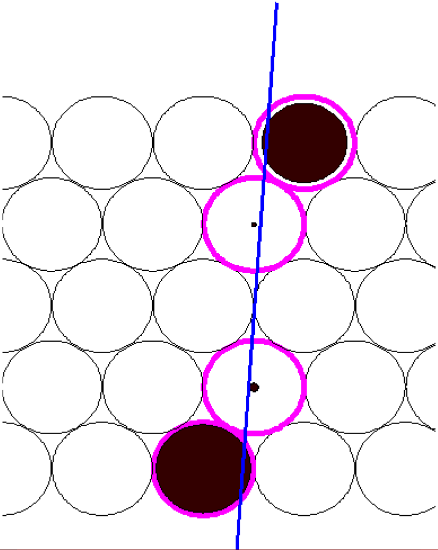
- Trained in Python/PyTorch: need to translate to C++
- Package of choice: *ONNXRunTime*
  - Highly optimized package to read ONNX files in C++
- Inference in C++ on CPU isn't the fastest: quantization/fusing layers!
- Able to get inference speed on data to 0.10 ± 0.01 ms/prediction
- Implementation:
  - If we have enough hits to infer: use ML predictions to fit (in local straw frame) to left/right of each hit (based on ML predictions)
  - Feed output of this to standard tracking pipeline

Performance on Simulation

- Wanted some comparisons of with and without ML
- Ran small simulation, ran tracking with and without ML interface
- Checked how often tracker got LR correct

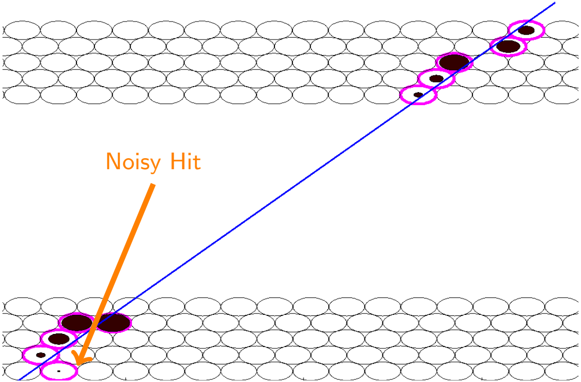
LR% Correct/Model	Without ML	With ML
Total	90.1%	92.6%
< 1mm	81.4%	82.2%
≥ 1mm	92.2%	95.0%
< 2.5mm	85.6%	87.7%
≥ 2.5mm	95.0%	97.6%
Vertical Straws	89.6%	93.3%
Horizontal Straws	90.9%	91.8%
LH Straws	91.5%	93.4%
LV Straws	88.1%	91.5%
RH Straws	90.1%	90.0%
RV Straws	91.0%	94.9%

STT Tracking: Back to the Failure



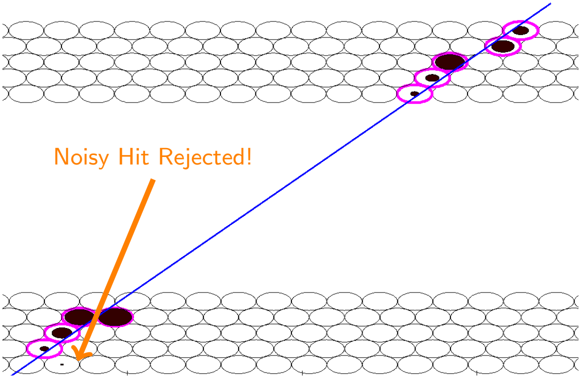
Noise Filtering

- Have an algorithm to group hits together - capable of some noise filtering and multi tracking
- Noise is too close to good hits - current algorithm fails
- True noise, multiple scattering, TTD inefficiency, etc.
- Want only best hits contributing to track to be given to ML



Better Noise Filtering

- Initial seed: OLS to straw centers
- Based on residual distribution from OLS fit: can reject hits as noise based on median average deviation (MAD)
- Takes χ^2_{red} of this track from $12.2 \rightarrow 0.8$!



- Machine learning is proving incredibly valuable in MUSE scattered particle tracking
- Enhancing the left-right ambiguity and noise filtering will only make our tracking stronger
- More improvements in both regards on the way!