Machine Learning in the MUSE Straw Tube Trackers

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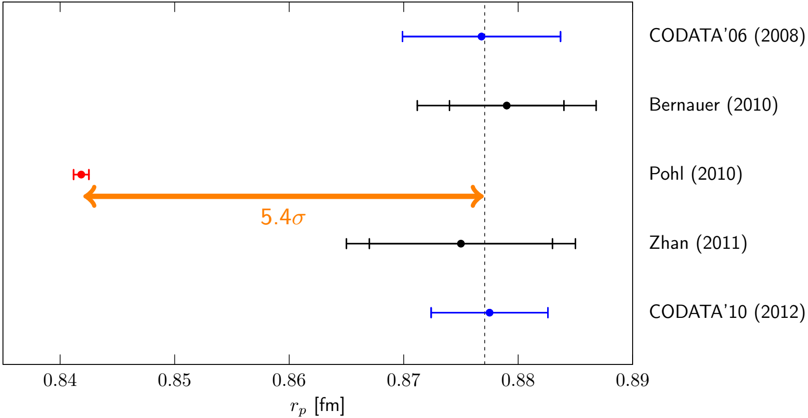
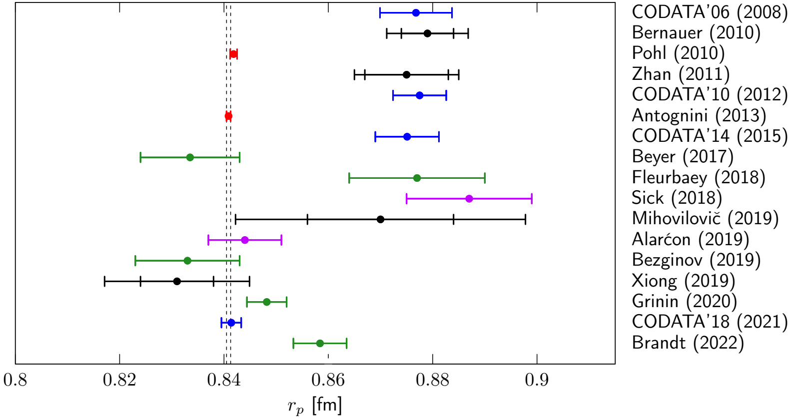
February 28, 2025

This material is based upon work supported by the National Science Foundation under NSF Grant PHY-2412703. The MUSE experiment is supported by the Department of Energy, NSF, PSI and the US-Israel Binational Science Foundation.

- 2010: CREMA collaboration measure Lamb Shift in muonic hydrogen
  - Results: $r_p = 0.84184 \pm 0.00067$ fm
- Average electron scattering measurement: ~ 0.877 fm



The Proton Radius Puzzle Today

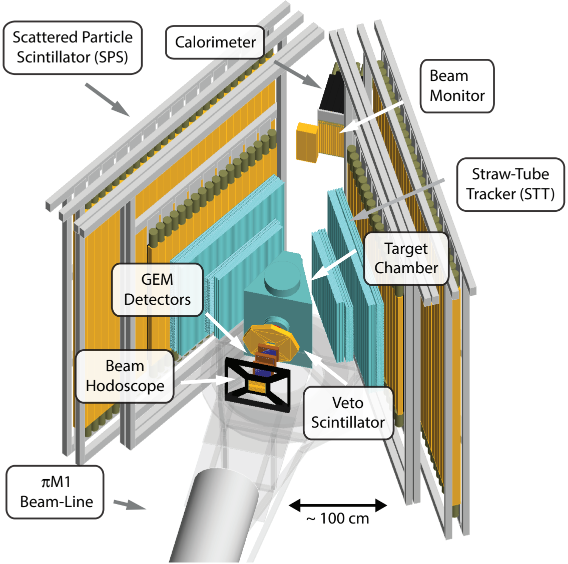


- Lepton universality?
- Radiative corrections (Two Photon Exchange (TPE))?
- Differences between spectroscopy and scattering?

The MUon Scattering Experiment (MUSE)

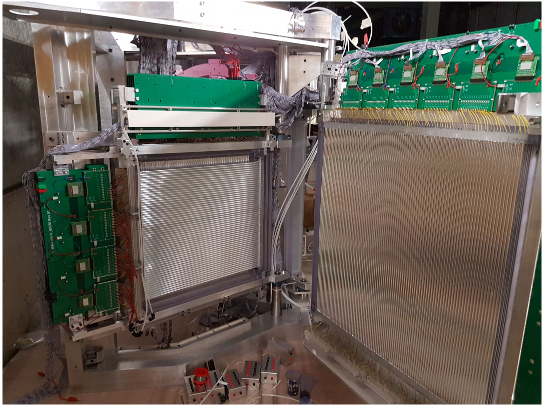
- The MUon Scattering Experiment (MUSE) was direclty inspired by the proton radius puzzle
- Goals:
  - Precision measurement of r_p via ep and μp scattering
  - Precision study of TPE in ep and μp scattering
  - Direct test of lepton universality
- Housed at the πM1 beamline at the Paul Scherrer Institute

- 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!



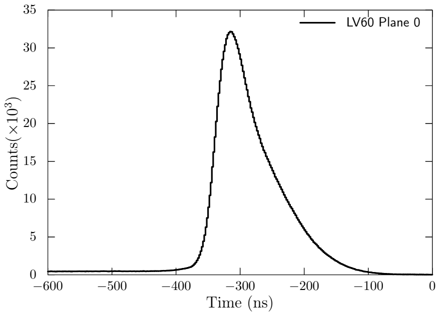
The Straw Tube Trackers (STT)

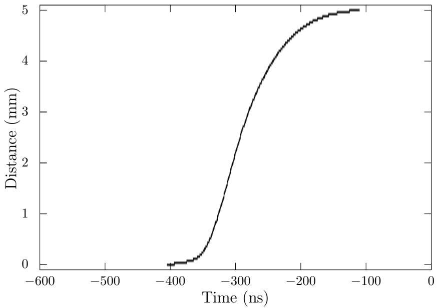
- Scattered particle tracking detector in MUSE
- Mirrored setup:
  - 20 planes of straws (10 horizontal, 10 vertical)
  - $\sim$ 3000 straws total!
  - Smaller front chamber, larger rear chamber
  - 5.1mm straw radius, 60 and 90 cm long
- Definition: set of 5 planes (so the 5 vertical horizontal, for example): "half chamber"



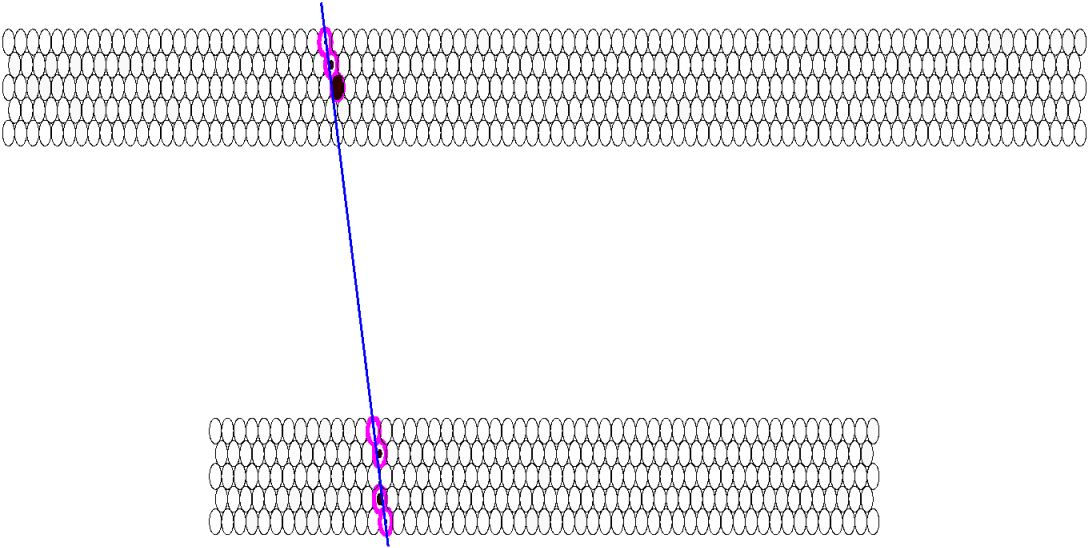
The Straw Tube Trackers (STT)

- "Standard" set of drift tubes
  - Measures time $\rightarrow$ distance, not (x, y, z)

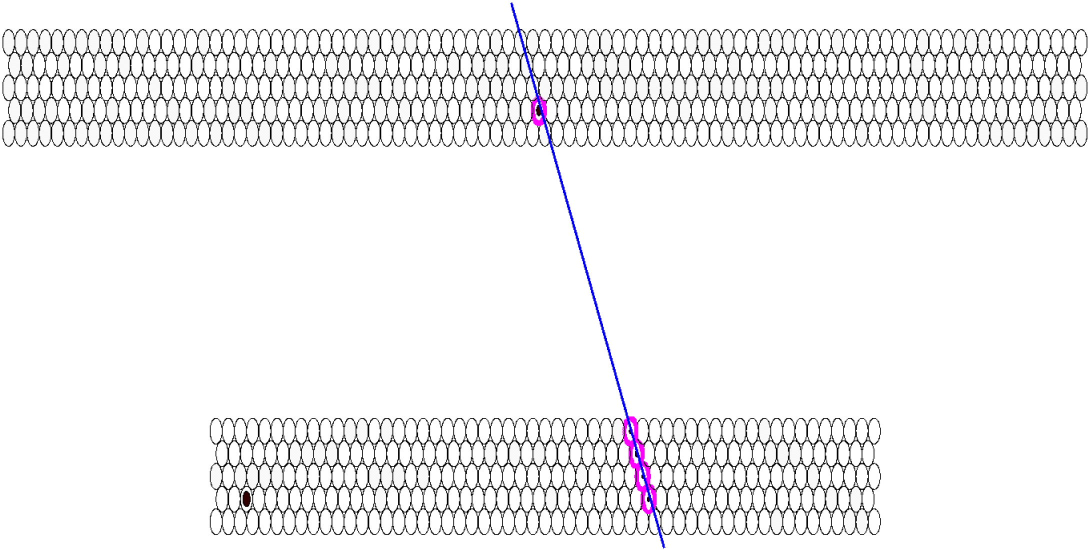




STT Tracking: Premise

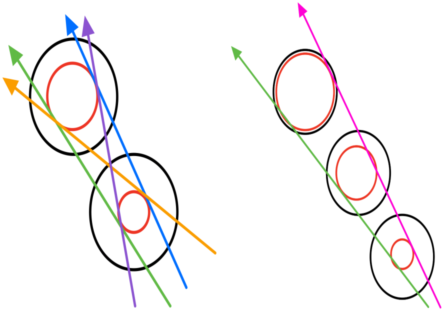


STT Tracking: Premise



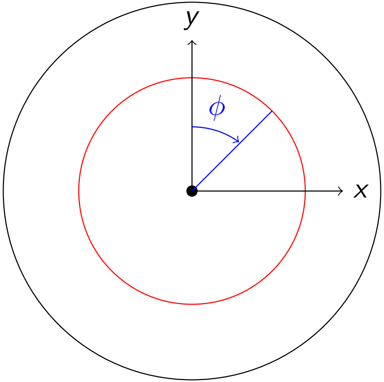
STT Tracking: Left Right Ambiguity

- Tracking is not straightforward: Left Right Ambiguity
- Makes χ^2 distribution in minimization complex
  - Many local minima for minimizer to get stuck in



Machine Learning Approach

- Idea: train a neural network to help resolve this ambiguity
- Few approaches to consider:
    - CNN to predict left/right alone
    - NN to predict ϕ in local straw frame
- Disclaimer: this is a work in progress!



Input Data

- For training: use Monte Carlo data
  - Generated 2 datasets: training and validation
  - Testing will be done later on run data
- Started with perfect radii, moved on to digitized/smeared
- Each "event" in the network:
  - At least 2 straws on a half chamber triggered by a primary particle
  - Direct input: 5 length 89 arrays; all 0 and radius of hit straws
  - Give the hit radius as well as the truth ϕ

```
plane,straw,real distance,phi

2,7,3.17937,1.34591

3,32,1.03686,1.19242
2,32,0.0207208,1.21275
1,31,1.61751,4.36256
0,31,3.17989,4.35121

4,21,1.10596,1.38557
1,21,2.0741,1.38562
3,21,2.11903,4.49986
0,22,2.25353,4.53246

0,54,1.94752,4.31264

1,0,3.01154,4.13951
0,1,2.2108,4.13119

3,12,0.93321,0.987719
4,12,0.252731,0.981482
1,13,1.97993,1.0019
```

NN Structure

- Structure of I/O:
  1. 5 arrays of length 89 (maximum straw in plane)
  2. All 0s (for loss masking) except for fired straws; these have their hit radii
  3. Concatenate all 5 arrays to form input
  4. Output: ϕ in radians, same concatenated form
- Training time for 100 epochs: ~ 12 minutes

```python
class LeftRightLearner(nn.Module):
    def __init__(self):
        super(LeftRightLearner, self).__init__()
        self.fc = nn.Sequential(
            nn.Linear(input_size, 2048),
            nn.BatchNorm1d(2048),
            nn.ReLU(),
            nn.Linear(2048, 1024),
            nn.BatchNorm1d(1024),
            nn.ReLU(),
            nn.Linear(1024, 256),
            nn.BatchNorm1d(256),
            nn.ReLU(),
            nn.Linear(256, input_size)
        )
    def forward(self, x):
        x = self.fc(x)
        return x % (2*torch.pi)
```

Custom Loss Function

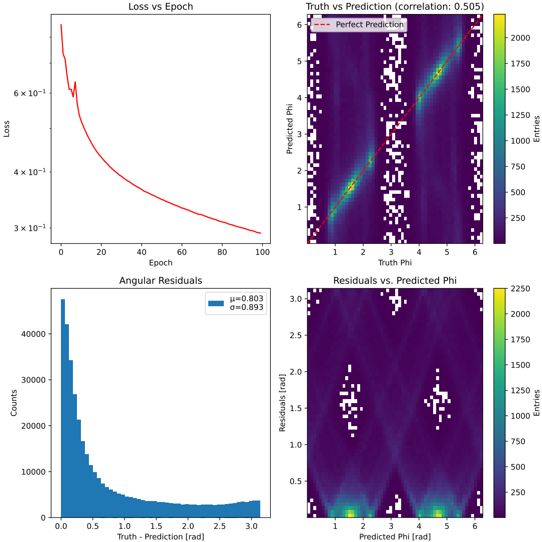
- Instead of ordinary MSE, defined my own
- Needed for angular differences wrapping around
  - For ordinary MSE: 1° and 359° have huge loss, but for this network it should be 2°

```
def MaskedCLLoss(truth, predicted):
    mask = (truth != 0)
    t, pred = truth[mask], predicted[mask]
    t, pred = t % (2*torch.pi), pred % (2*torch.pi)
    loss = torch.mean(1-torch.cos(t-pred))
    return loss
```

Training Tools

- Complex structure - use a learning rate scheduler
- Tested a few, chose "CosineAnnealingWarmRestarts"
  - Method of torch.optim.lr_scheduler
  - After T_0 epochs, resets the learning rate
  - This resetting happens every $T_0 + T_0 * T_{\text{mult}}$ epochs
  - Can set minimum learning rate
- Very large datasets - running using cuda

Results



Loss vs Epoch
Loss
Epoch
6×10^{-1}
4×10^{-1}
3×10^{-1}
Truth vs Prediction (correlation: 0.505)
Perfect Prediction
Predicted Phi
Truth Phi
Entries
Angular Residuals
μ=0.803
σ=0.893
Counts
Truth - Prediction [rad]
Residuals vs. Predicted Phi
Residuals [rad]
Predicted Phi [rad]
Entries

Thoughts

- NN seems to be progressing in right direction, but exists plenty of room for improvement
- Structure of NN is rather complex, potentially can be simplified
    - As well, may replace the hit radius on input with simply 1
- Bigger picture: implemtation in tracking code
    - Since we know r and $\phi \rightarrow (x, y)$ in local frame, can convert this to a hit in global frame
    - Write a simpler minimizer to take this information and fit a seed to these positions, give this seed to minimizers

Conclusions/Future

- Proof of concept for using NN to assist STT tracking showing proimise
- Will be tested on real data soon
- Future work:
  - Test on real data
  - Optimize network
  - Implement in tracking code
- Any comments/suggestions are welcome!

Form Factor Discrepancies