Machine Learning in the MUSE Straw Tube Trackers: Update 1

Kyle Salamone

Center for Frontiers in Nuclear Science, Stony Brook University

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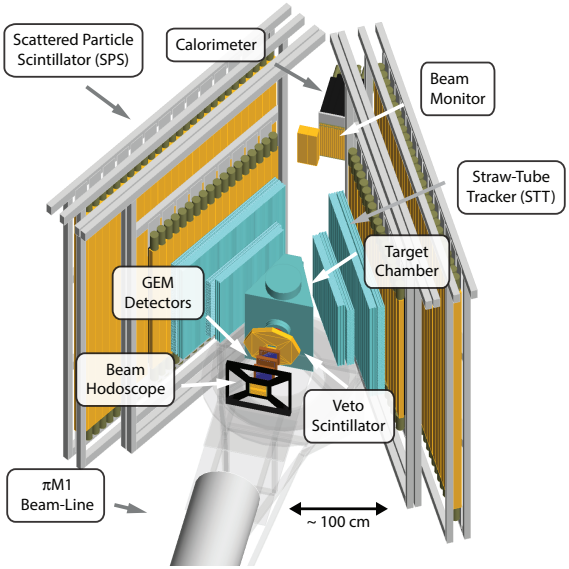
The MUon Scattering Experiment (MUSE)

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

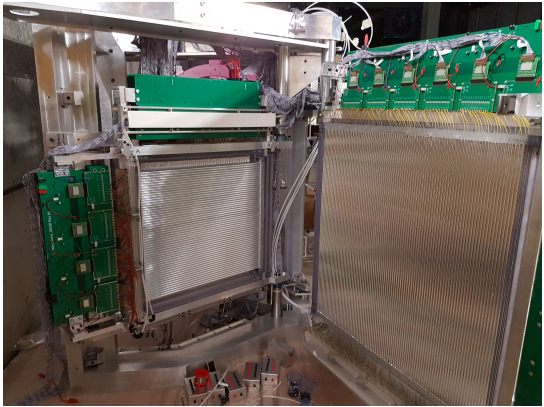
Experimental Setup

- 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!



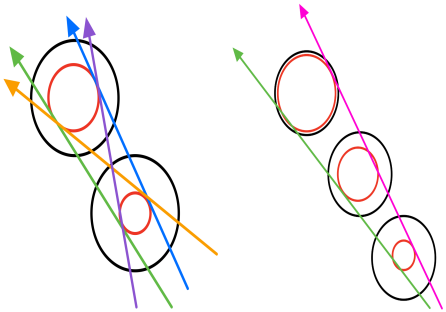
The Straw Tube Trackers (STT)

- 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



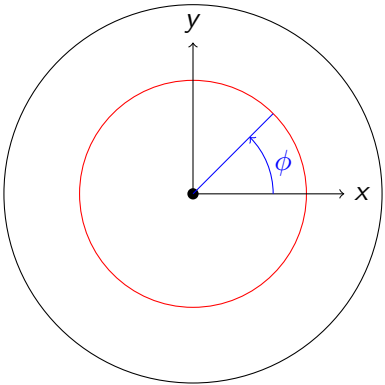
STT Tracking: Left Right Ambiguity

- 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
- NN to predict ϕ in local straw frame
  - More accurately: predict $(\sin(\phi), \cos(\phi))$

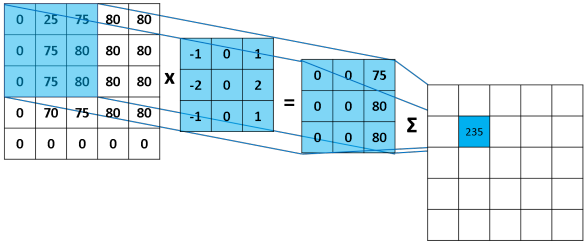


Training Tools

- Convolutional Neural Network structure (CNN)
- CosineAnnealingWarmRestarts LR scheduler
- Adam optimizer
- Loss function: custom wrapper around SmoothL1Loss for masking

Convolutional Layers

- Extract certain features from “image” like input
- Definitions:
  - Channels: specific feature or characteristic of the image
  - Kernel size: how big each “picture” is
  - Padding: pad input dimension with zeros
  - Stride: how many pixels we move the kernel per “step”
- Idea: treat planes of straws as 2D image



https://mlnotebook.github.io/post/CNN1/

NN Structure

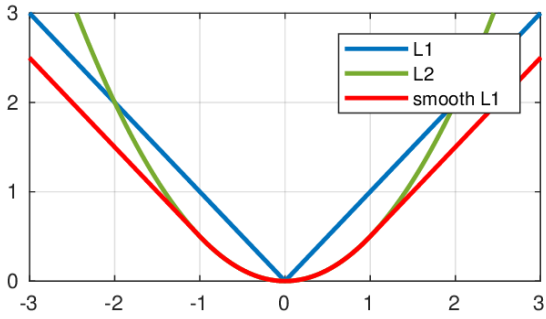
```python
class LeftRightLearner(nn.Module):
    def __init__(self):
        super(LeftRightLearner, self).__init__()
        self.fc = nn.Sequential(
            nn.Conv2d(in_channels=2,out_channels=128, kernel_size=(5,10), stride=(5,5), padding=(0,3)),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Conv2d(in_channels=128, out_channels=256, kernel_size=1),
            nn.ReLU(),
            nn.Dropout(0.2),
            nn.Flatten(),
            nn.Linear(9216, 1024),
            nn.ReLU(),
            nn.Linear(1024, 2*input_size)
        )
    def forward(self, x):
        return self.fc(x)
```

- Structure of I/O:
  1. 10 arrays of length 89
  2. 2 input channels: binary 0/1, hit radius
  3. Output: $(\sin(\phi), \cos(\phi))$
- Training* time for 70 epochs with CUDA: $\sim$ 16.5 minutes

SmoothL1Loss

- Combines L1 (linear) and L2 (quadratic) loss functions
- β: hyperparameter, defines transition point
- Benefits: less sensitive to outliters than MSE, *can* prevent exploding gradients

$$\text{loss}(x, y) = \begin{cases} 0.5\,(x_n - y_n)^2 / \beta & \text{if} |x_n - y_n| < \beta \\ |x_n - y_n| - 0.5\beta & \text{otherwise} \end{cases}$$

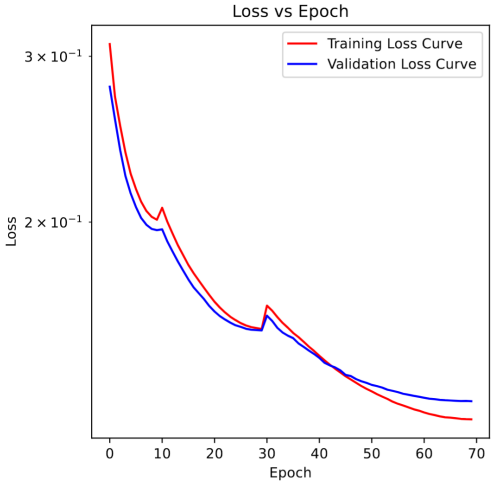


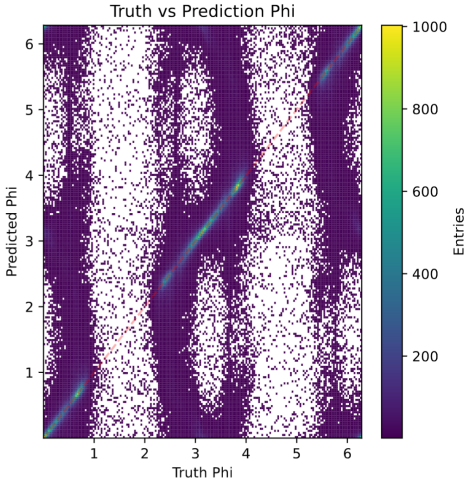
https://www.researchgate.net/figure/Plots-of-the-L1-L2-and-smooth-L1-loss-functions_fig4_321180616

Loss Function

```python
def MaskedTrigLoss(truth, predicted):
    mask = (truth != 0)

    sin_pred, cos_pred = predicted[:, :890], predicted[:,890:]
    sin_pred, cos_pred = sin_pred[mask], cos_pred[mask]
    sin_true, cos_true = torch.sin(truth[mask]), torch.cos(truth[mask])

    sin2_cos2 = torch.square(sin_pred) + torch.square(cos_pred)
    sin2_cos2_true = torch.ones_like(sin2_cos2)

    pred_vec = torch.stack([sin_pred, cos_pred, sin2_cos2], dim=1)
    true_vec = torch.stack([sin_true, cos_true, sin2_cos2_true], dim=1)

    return nn.SmoothL1Loss(beta=0.5)(pred_vec, true_vec)
```

Results





Results are on the validation set, not the training set.

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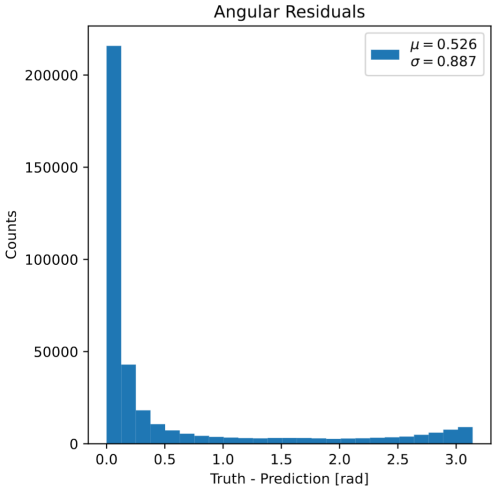

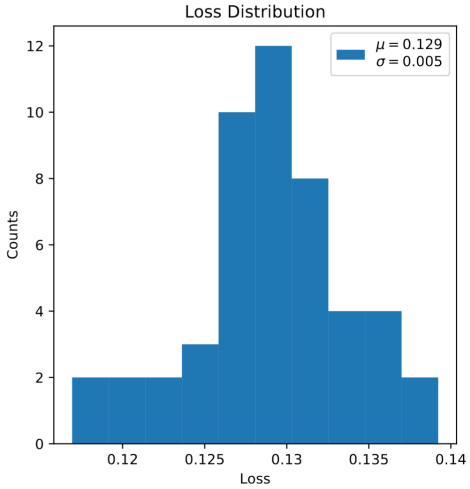

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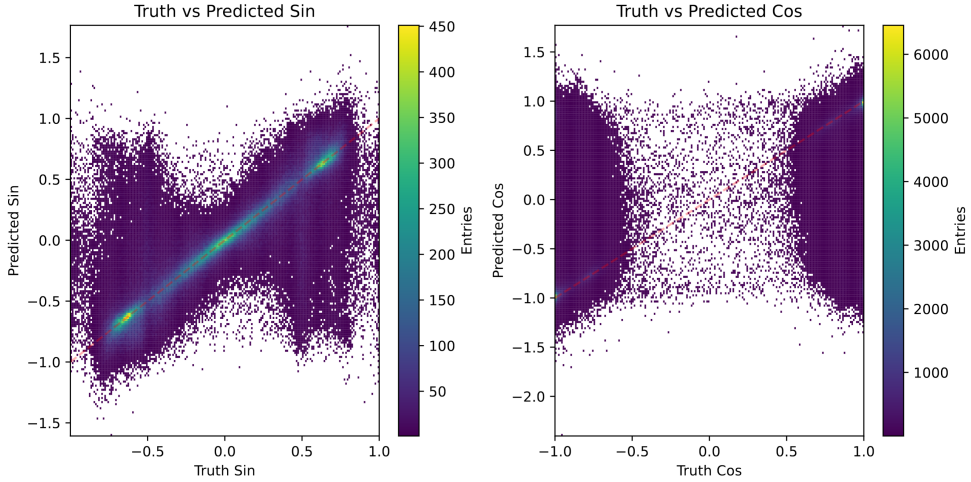

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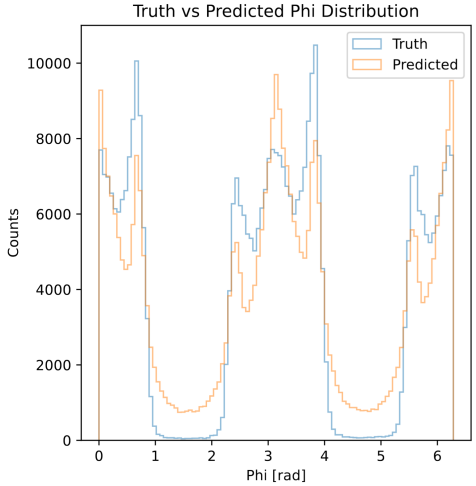

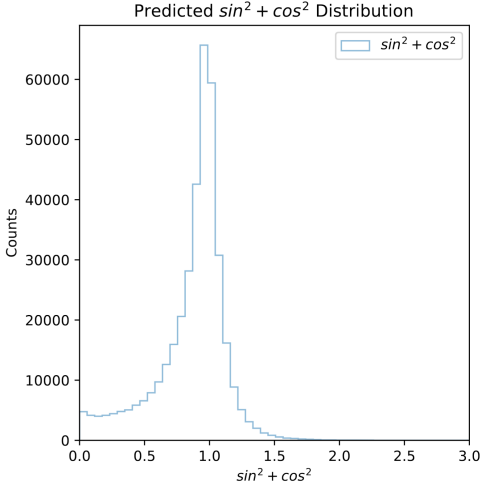

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Thoughts

- Results are very promising
- Based on loss curves - not done training!
- Can test on run data, seems to perform okay (far from perfect) - implementation in main code...

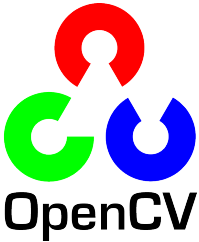
Data Results

```
Testing model...
Model inference took 0.018435376001434634 seconds.
Plane 1, Straw 33: Truth: 0.541, Prediction: 2.987 Difference 2.446
Plane 2, Straw 34: Truth: 0.541, Prediction: 3.938 Difference 2.887
Plane 3, Straw 34: Truth: 0.541, Prediction: 4.603 Difference 2.222
Plane 4, Straw 35: Truth: 0.541, Prediction: 0.067 Difference 0.475
Plane 6, Straw 44: Truth: 0.541, Prediction: 0.548 Difference 0.007
Tested!
Testing model...
Model inference took 0.0007275600000866689 seconds.
Plane 1, Straw 17: Truth: 3.672, Prediction: 3.778 Difference 0.106
Plane 3, Straw 15: Truth: 0.531, Prediction: 0.558 Difference 0.027
Plane 5, Straw 11: Truth: 3.672, Prediction: 3.723 Difference 0.051
Plane 6, Straw 10: Truth: 3.672, Prediction: 3.578 Difference 0.094
Plane 7, Straw 10: Truth: 3.672, Prediction: 3.819 Difference 0.147
Plane 9, Straw 9: Truth: 3.672, Prediction: 6.050 Difference 2.377
Tested!
```

```
Testing model...
Model inference took 0.0006295849998423364 seconds.
Plane 0, Straw 28: Truth: 3.678, Prediction: 0.349 Difference 2.954
Plane 1, Straw 27: Truth: 3.678, Prediction: 0.221 Difference 2.826
Plane 3, Straw 26: Truth: 3.678, Prediction: 1.044 Difference 2.635
Plane 5, Straw 21: Truth: 3.678, Prediction: 2.633 Difference 1.046
Plane 6, Straw 20: Truth: 3.678, Prediction: 0.706 Difference 2.972
Plane 7, Straw 20: Truth: 3.678, Prediction: 0.809 Difference 2.869
Plane 9, Straw 19: Truth: 3.678, Prediction: 0.397 Difference 3.002
Tested!
```

C++ Implementation

- Trained model in Python, analysis code in C++/ROOT
- Many methods tested to implement...
  - Torch C++ API
  - onnx2code
  - ONNXRuntime
  - ROOT TMVA/SOFIE
- Tested all on performance, ease of use: decided on *OpenCV*



Sample OpenCV Code

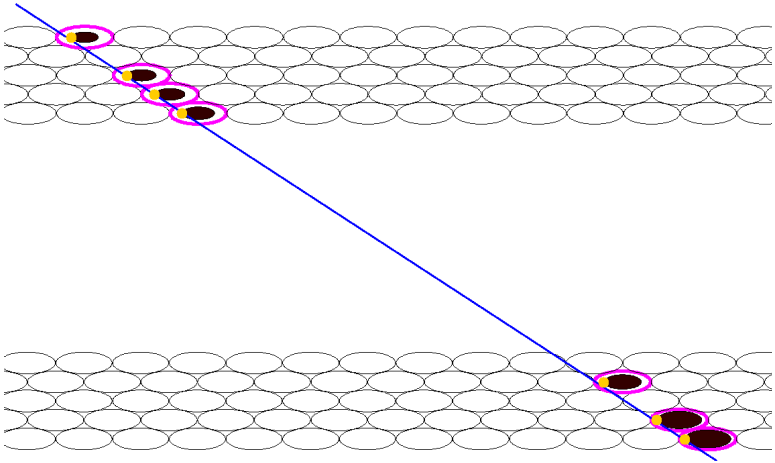
```cpp
std::string model_path = "line_model_10.onnx";
cv::dnn::Net model = cv::dnn::readNetFromONNX(model_path);
model.setPreferableBackend(cv::dnn::DNN_BACKEND_OPENCV);
model.setPreferableTarget(cv::dnn::DNN_TARGET_CPU);
cv::setNumThreads(1);
std::array<int, 4> input_shape = {1, 2, 10, 89};
cv::Mat input_mat = cv::Mat::zeros(4, input_shape.data(), CV_32F);
```

```cpp
std::vector<size_t> good_indices;
for(int k=0;k<10;k++)
{
    for(int l=0;l<89;l++)
    {
        int flat_index = l + 89*k;
        if(input[0][0][k][l] > 0.f) good_indices.push_back(k*89 + l);
        input_mat.at<float>(flat_index) = input[0][0][k][l];
        input_mat.at<float>(flat_index + 89*10) = input[0][1][k][l];
    }
}

std::vector<std::string> outLayerNames = model.getUnconnectedOutLayersNames();
model.setInput(input_mat);
std::vector<cv::Mat> result;
model.forward(result, outLayerNames);
```

Tracking Implementation

- Prediction gives set of points that lie on each drift tube - fit this to a line $\rightarrow$ seed for full fit!



Conclusions/Future

- Predictor CNN progressing very well
- Needs to be trained on more simulated data
- Fine tune NN structure, hyperparameters, loss function, etc.
- Work on optimizing C++ implementation