Deep Learning Based Tracking Reconstruction and Magnetic Field Measurement Research in the Muon g-2 Experiment

ID. 42

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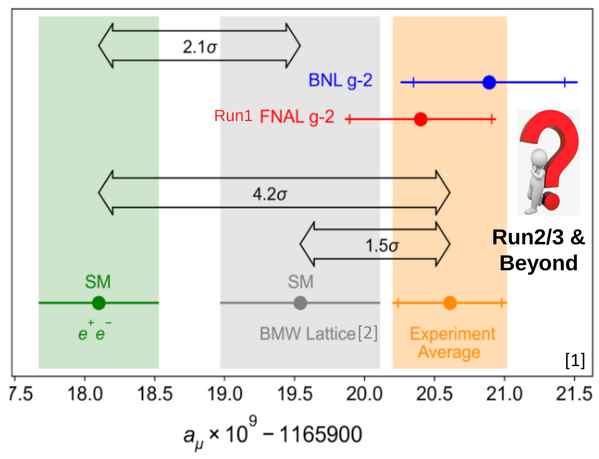
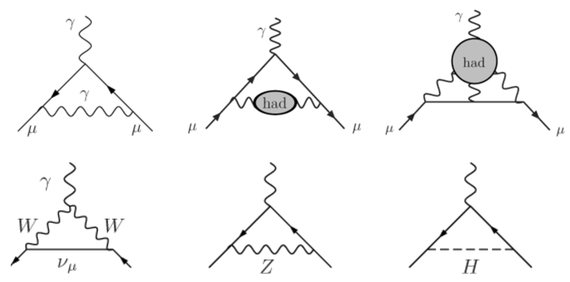
Solving a Long Pursuing Mystery



a_μ(FNAL) = 116 592 040 (54)×10^{-11} (0.46ppm)

a_μ(Exp) = 116 592 061 (41)×10^{-11} (0.35ppm)



[1] Phys. Rev. Lett. 126, 141801 (2021)

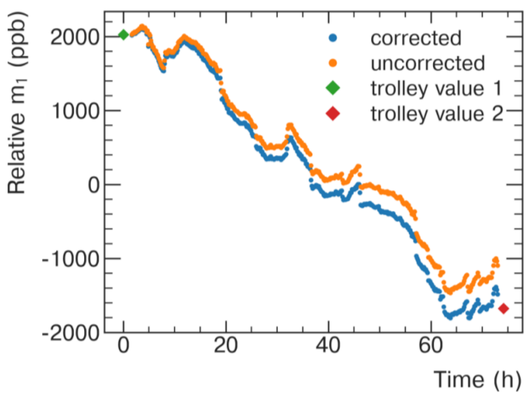
[2] Nature 593, 51–55 (2021)

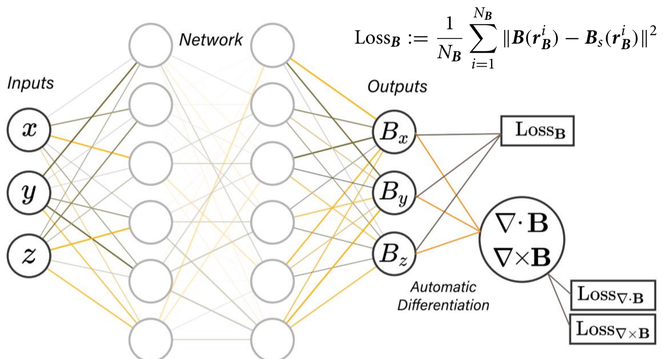
Magnetic Field Measurement

- Muon g-2 experiment requires precision $\boldsymbol{B}$ field measurement
- Pulsed NMR probes measure the $\boldsymbol{B}$ field ($\omega_p = \frac{2\mu_p}{\hbar}|\boldsymbol{B}|$)

$$|B| \approx B_y = A_0 + \sum_{n=1} (\frac{r}{r_0})^n [A_n \cos(n\theta) + B_n \sin(n\theta)]$$

- Trolley probes map the field / Fixed probes track the field drift
- The calibration between trolley/fixed measurements are not constant
- Imperfect field tracking lead a sync-offset between field mapping





$$\text{Loss}_B := \frac{1}{N_B}\sum_{i=1}^{N_B} \|\boldsymbol{B}(\boldsymbol{r}_B^i) - \boldsymbol{B}_s(\boldsymbol{r}_B^i)\|^2$$

Scientific Reports volume 12, Article number: 12858 (2022)

$$\text{Loss}_{\nabla\cdot B} := \frac{1}{N_f}\sum_{i=1}^{N_f} |\nabla\cdot\boldsymbol{B}(\boldsymbol{r}_d^i)|^2$$

$$\text{Loss}_{\nabla\times B} := \frac{1}{N_f}\sum_{i=1}^{N_f} \|\nabla\times\boldsymbol{B}(\boldsymbol{r}_d^i)\|^2$$

- PINN (physics informed neural network): data + physical laws
- Embed the Maxwell's equation into the loss via automatic differentiation

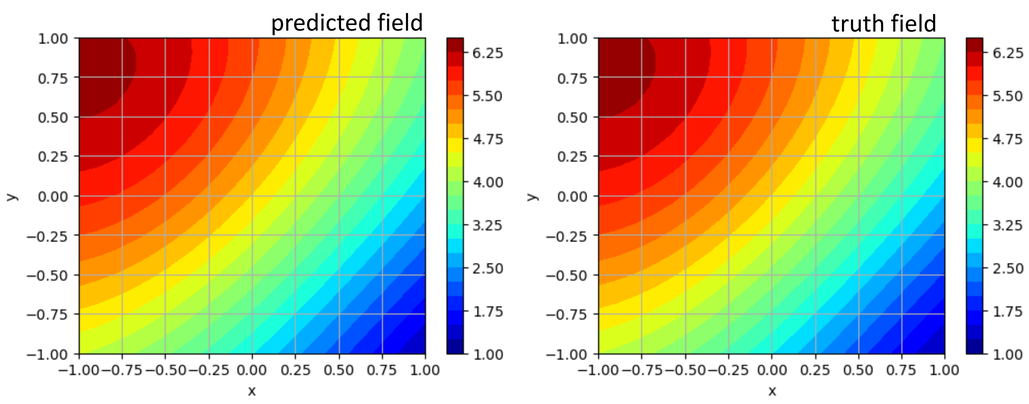
$$\nabla\cdot B = 0 \qquad \nabla\times B = 0$$

- First repeat the prediction model in simulation data:
  - Using 8 coils (radius=1) to generate the magnetic field
  - Predict the field in a box (2×2×2) region using the surface samples

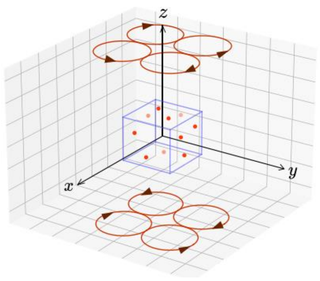
$$\begin{cases} B_x = C\dfrac{xz}{2\alpha^2\rho^2\beta}\left[(a^2+r^2)E(k^2) - \alpha^2 K(k^2)\right] \\ B_y = \dfrac{y}{x}B_x \qquad k^2 = \dfrac{4ar\sin\theta}{a^2+r^2+2ar\sin\theta} \\ B_z = C\dfrac{1}{2\alpha^2\beta}\left[(a^2-r^2)E(k^2) + \alpha^2 K(k^2)\right] \end{cases}$$

- Field at (x, y, z) generated by a current loop with radius a
- K, E are the elliptic integrals

$$\rho^2 \equiv x^2+y^2,\ \alpha^2 \equiv a^2+r^2-2a\rho$$
$$\beta^2 \equiv a^2+r^2+2a\rho \qquad z = r\cos\theta$$
$$r \equiv \sqrt{x^2+y^2+z^2}$$



ΔB	center	1unit shift	2units shift
Mean	6.5×10^{-4}	4.7×10^{-4}	1.7×10^{-2}
std	8.5×10^{-3}	2.5×10^{-2}	7.8×10^{-2}



Summary & Further Plan (Magnetic Field):

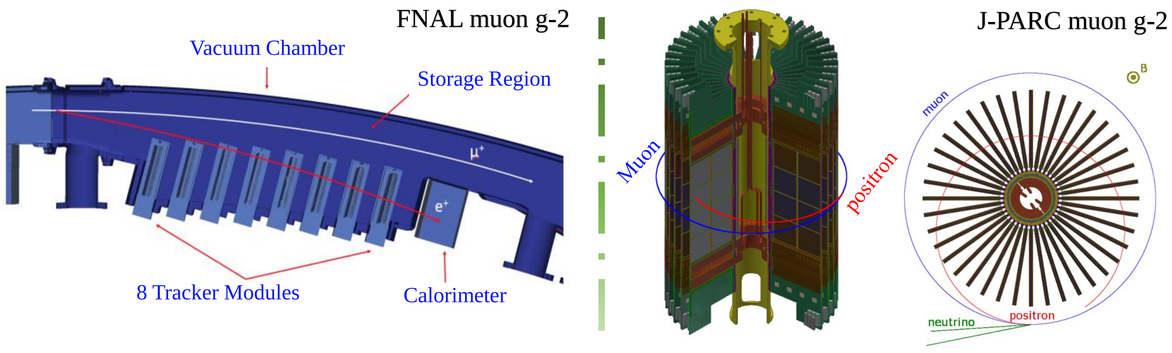
- The PINN-based model predicts the magnetic field with a small data size
- The model shows enormous potential in field tracking problems
- Next to set the coils the same geometry as muon g-2 experiment
- Need comparison with the multipole moment fitting method

Muon g-2 Experiment

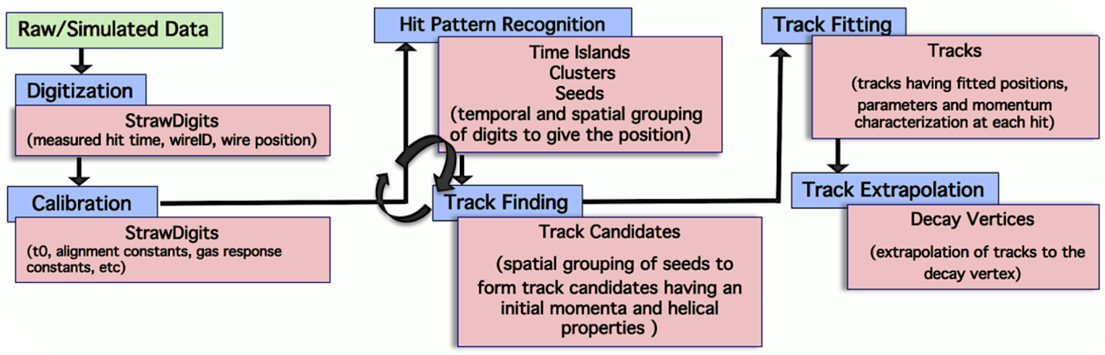
	Fermilab	J-PARC g-2/EDM	HIAF(Prospect)
POT per pulse	~10^{12}	~10^{15}	~10^{14}
Pulse width	120ns	100ns	~200-300ns
Frequency	12Hz	25Hz	>5Hz
Proton beam momentum	8GeV/c	3GeV/c	~10GeV/c
Muon Momentum	3.094GeV/c	300MeV/c	~3.5GeV
Number of detected e$^+$	1.6×10^{11} (1x)	5.7×10^{11} (3.5x)	~49×10^{11} (30x)
Statistical uncertainty	100ppb	450ppb	~18ppb
Systematic uncertainty	100ppb	<70ppb	<70ppb

- Higher intensity experiment producing more data, challenging in processing data with high speed and efficiency
- Machine learning (ML) techniques can be of big help, need to fully explore more and further

Tracking Reconstruction



- 2 tracker stations × 8 modules × 2 planes × 2 layers × 32 straw tube (FNAL)
- 40 radial modules × 16 sensors × 2 blocks × 512 strips (from J-PARC TDR)

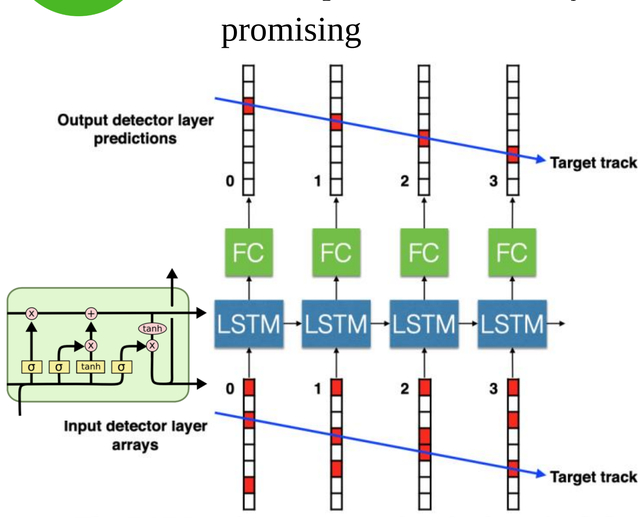


Fermilab Muon g-2 tracking reconstruction workflow

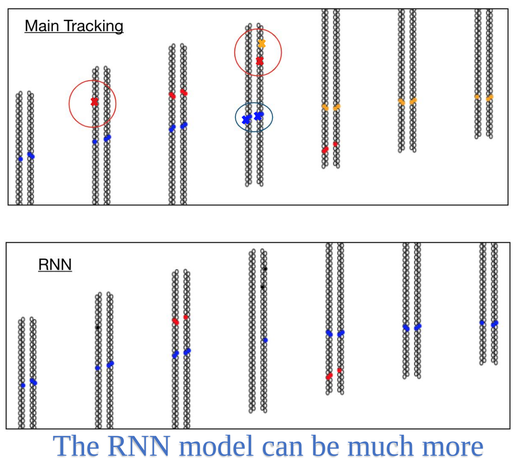
- Only long tracks are reconstructed (>5 planes)
- Tracking is >50% of total recon time
- Low efficiency after quality cut (8% in Run1, ~28% Run2/3)*

*FNAL Muon g-2 internal note:266

- Preliminary study using deep learning techniques (RNN+LTSM) were tried and tested with Fermilab g-2 experiment setup [2]
- Test in pseudo-data and synthetic datasets, and the results were promising



The RNN architecture used to find tracks [1]



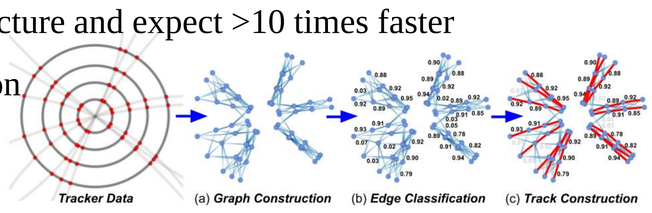
The RNN model can be much more intelligent in complicated events [2]

[1] The HEP.TrkX Project: deep neural networks for HL-LHC online and offline tracking

[2] https://github.com/ManolisKar/ML_tracking

Summary & Further Plan (Tracking):

- The LSTM-based model shows an enormous potential in tracks finding
- The RNN architecture cannot handle the data parallelly and still limited by speed
- Plan to develop GNN-based architecture and expect >10 times faster
- Plan to explore the model application in J-PARC muon g-2 experiment



Take from https://iris-hep.org/projects/accel-gnn-tracking.html