First Europe-China-Japan Workshop on Muon Physics: Synergies in g-2, MUonE and Beyond

AI-Enhanced Magnetic Field Measurements

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Outline

- Motivations
- Machine Learning Method Principle to Measure the Magnetic Field: PINN
- Simulation Data Generation and Validation
- Experimental Data: Helmholtz Coils and Sliding Table System
- Preliminary Data Analysis
- Summary and Outlook

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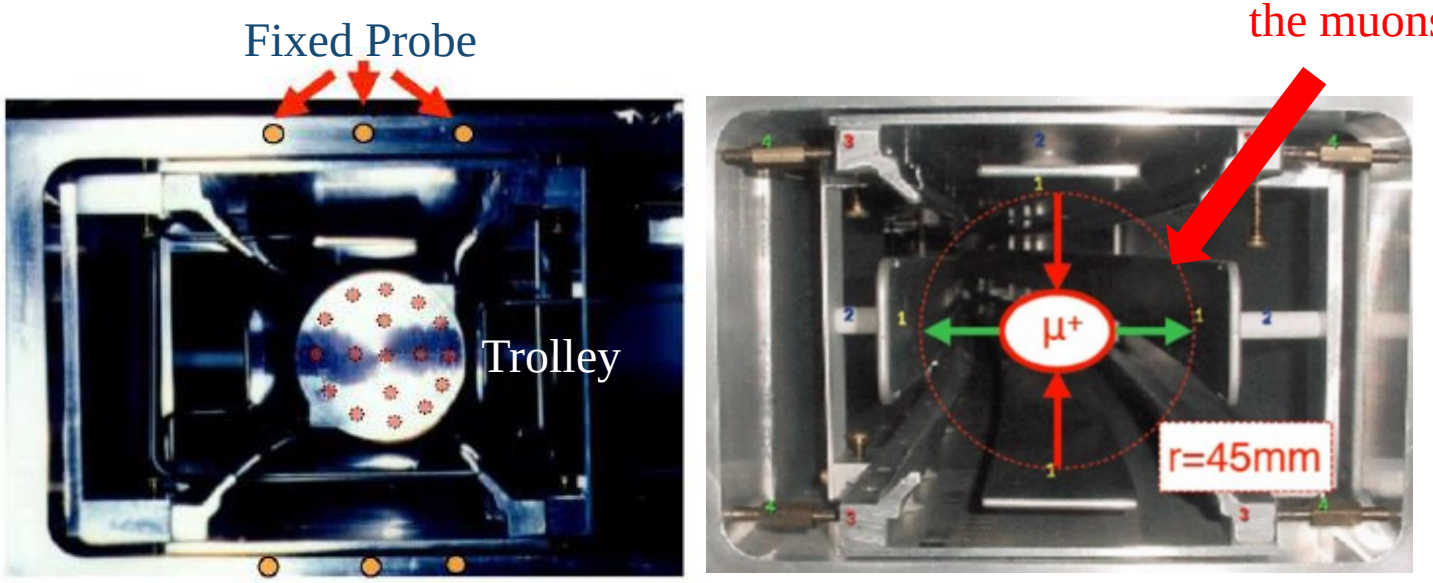
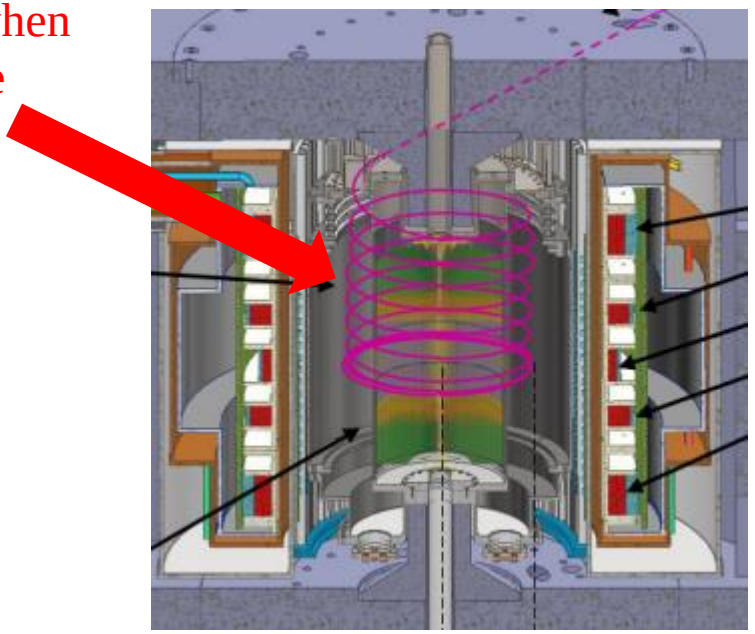
Motivation

- Muon g-2 experiment: magnetic field within experimentally inaccessible region is hard to determine
  - Muon production / storage region when the beam is on
- Need to use magnetic probes and do the interpolation
- Limited number of probes effect the precision of the measurements



Fermilab muon g-2 storage region

Inaccessible region when the muons are storage



J-PARC muon g-2 storage region

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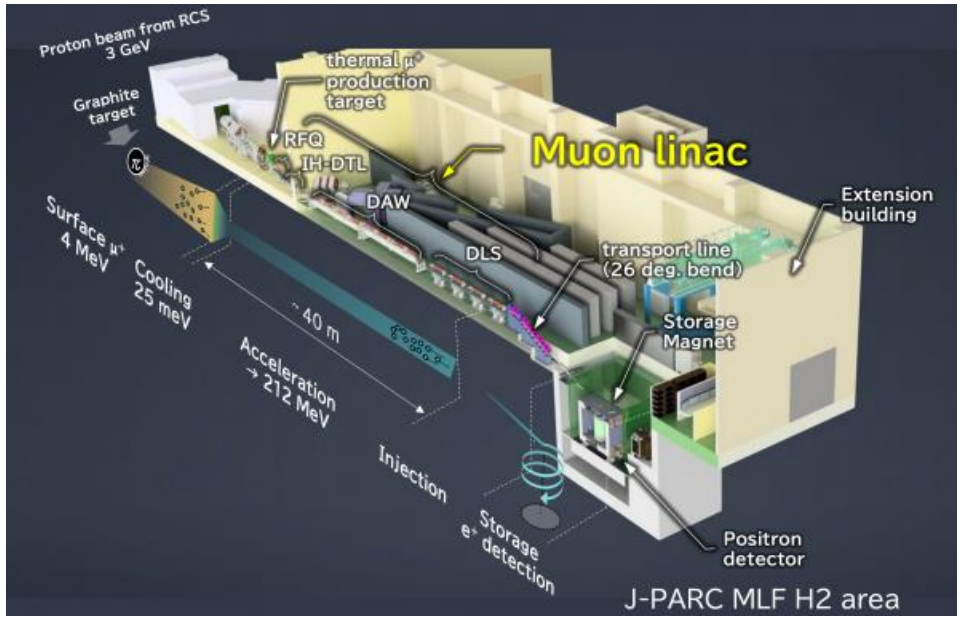
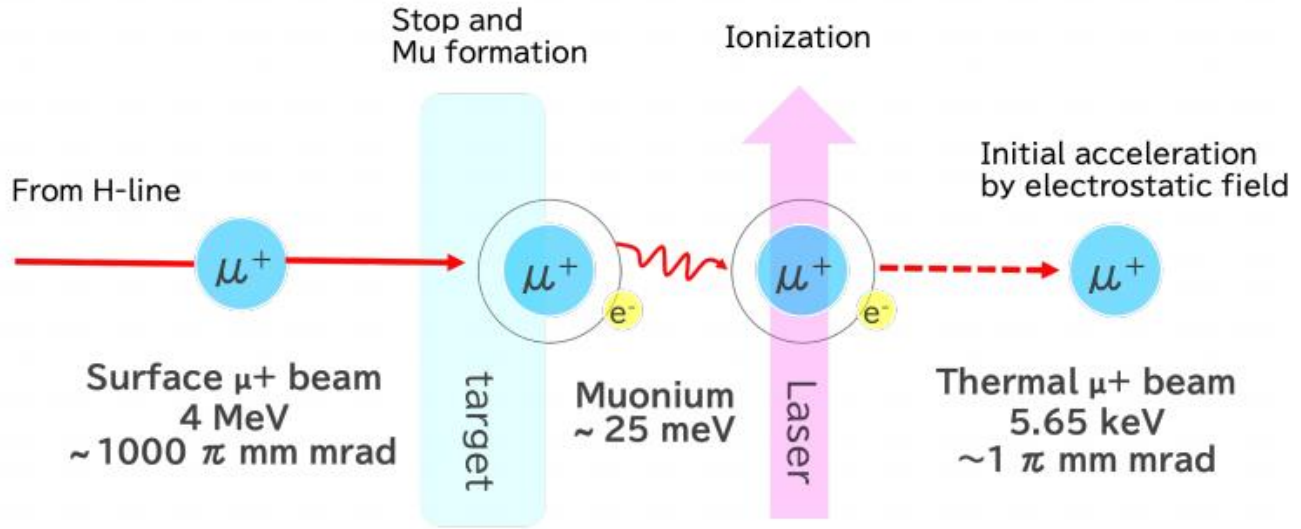
Motivation

- Magnetic field need also to be precisely controlled in the muon production region (J-PARC)





- Muonium's spin direction is easily disturbed by the surrounding magnetic field (e.g., geomagnetic ~60 μT)
- The ambient magnetic field must be controlled below ±1 μT to preserve the Mu spins
- Minimize beam shift due to the ambient magnetic field by controlling the magnetic field

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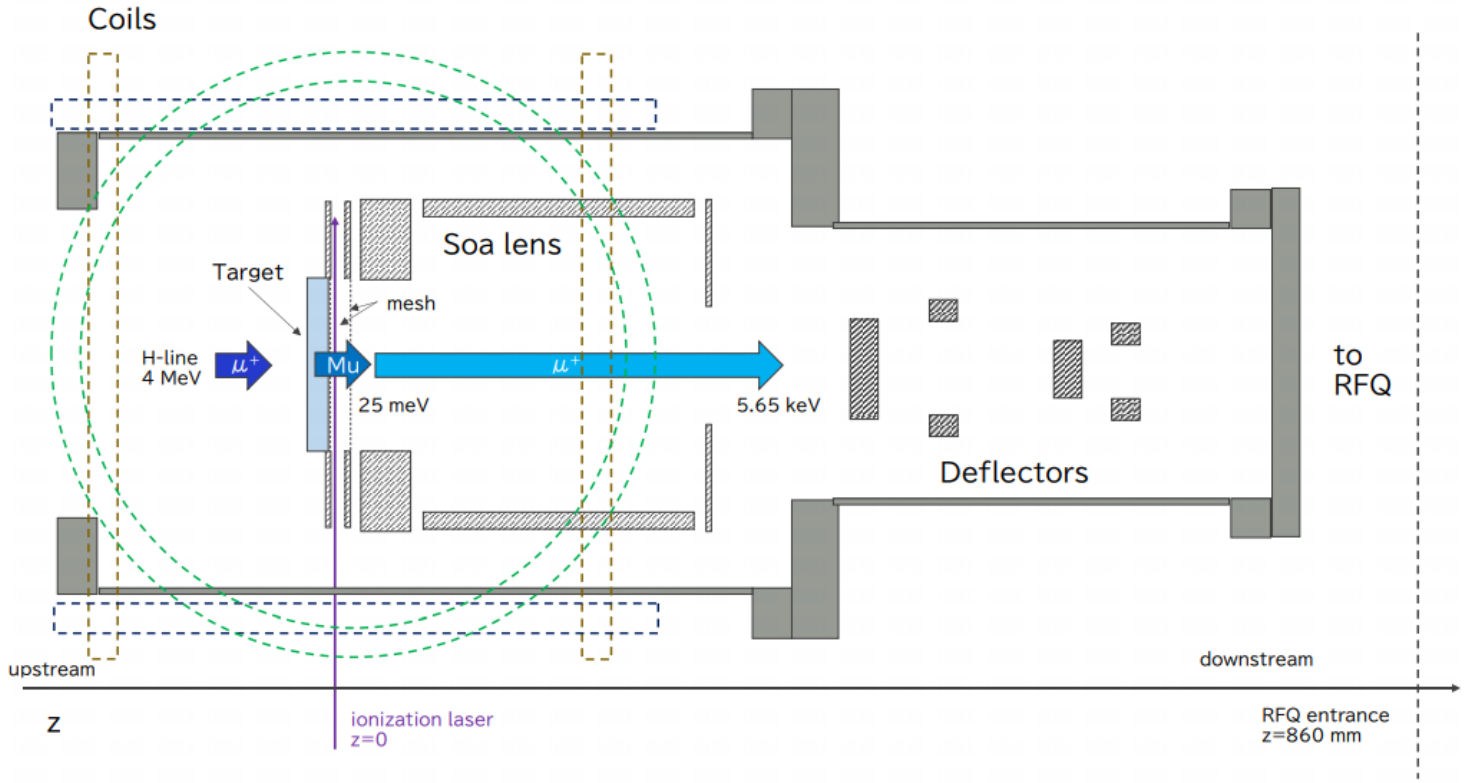
Motivation

- 3 Helmholtz coils are designed to cancel the surrounding magnetic field
  - geomagnetic
  - magnet from nearby experiments
- Develop an AI-Enhanced magnetic field measurement to help the monitoring



Multipole expansion method.

- The magnetic field vector can be written as a gradient of a scalar magnetic potential function:

$$\boldsymbol{B} = -\nabla \Phi_M(\boldsymbol{r})$$

- The magnetic scalar potential satisfies Laplace's equation:

$$\nabla^2 \Phi_M = 0$$

- the solution of Laplace's equation in spherical coordinates is given by:

$$\Phi_M(r,\theta,\phi) = \sum_{l}^{\infty} \sum_{m}^{l} r^l P_l^m(\cos\theta)[a_{lm}\cos(m\phi) + b_{lm}\sin(m\phi)]$$

- where P_l^m are the associated Legendre polynomials, and a_{lm} and b_{lm} are expansion coefficients
- Absorbing a_{lm} and b_{lm} in a coefficient c_n, we can write the magnetic field in a compact form

$$\boldsymbol{B}(x,y,z) = \sum_{n} c_n \boldsymbol{f}_n(x,y,z)$$

➢ B field multipole expansion in the Fermilab muon g-2 experiment

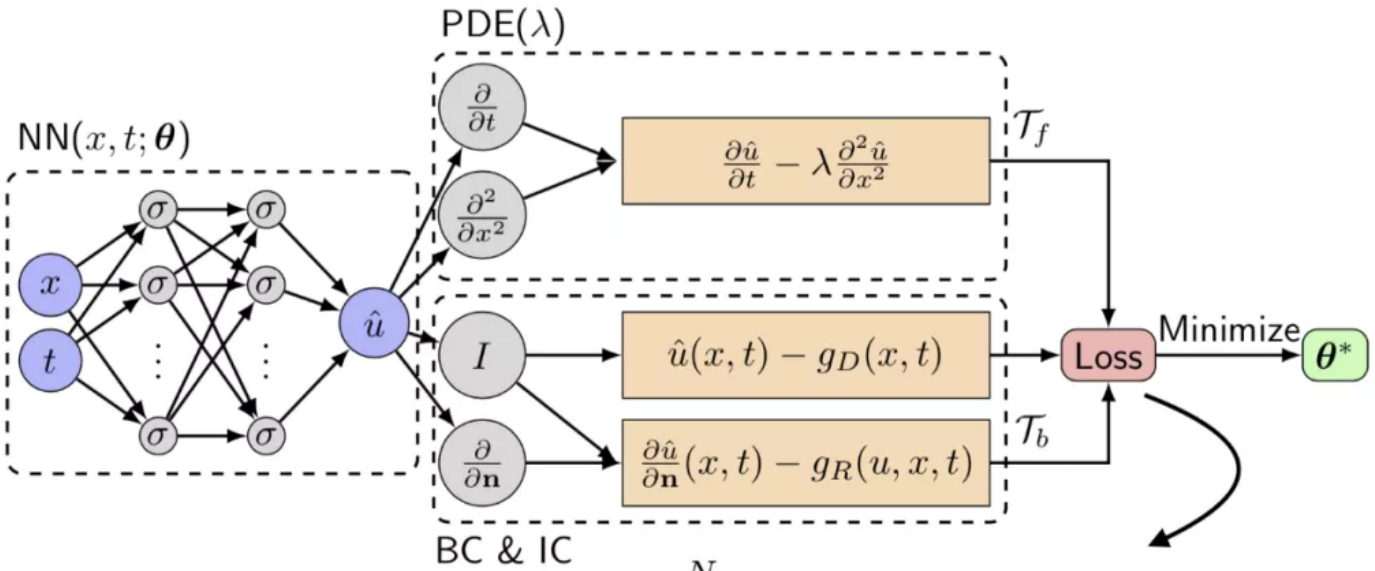
$$B_y = a_0 + \sum_{n=1}^{\infty} (r/r_0)^n [a_n cos(n\theta) + b_n sin(n\theta)]$$

	f_0	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9
x	0	-1	0	$-x$	$-3z$	0	$6x$	$6y$	$-3xz$	$\frac{3}{2}(3x^2+y^2-4z^2)$
y	0	0	-1	$-y$	0	$-3z$	$-6y$	$6x$	$-3yz$	$3xy$
z	1	0	0	$2z$	$-3x$	$-3y$	0	0	$-\frac{3}{2}(x^2+y^2-2z^2)$	$-12xz$

the first 10 f_n basis vector functions

AI-Enhanced Method: PINN

- PINN: Physics Informed Neural Network
- A popular method for recent years in fluid mechanics area
- Aim to solve a set of PDE (partial differential equations)

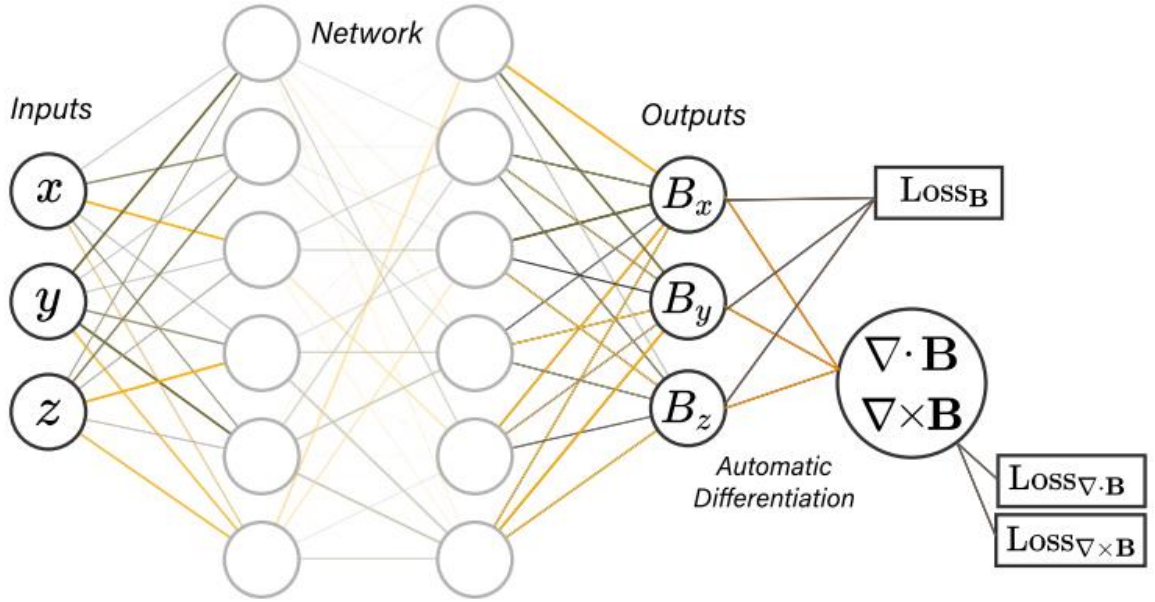


$$\mathcal{L}(\theta) := \underbrace{\frac{1}{N_u}\sum_{i=1}^{N_u}[\boldsymbol{u}_i - f_\theta(\boldsymbol{x}_i)]^2}_{\text{Data fit}} + \underbrace{\frac{1}{\lambda}\mathcal{R}[f_\theta(\boldsymbol{x})]}_{\text{Physics regularization}}$$

AI-Enhanced Method: PINN

- Maxwell equation is also PDE
- Assuming there are no free currents (J=0) and no magnetization M=0, the Maxwell equation is:

$$\nabla \cdot \boldsymbol{B} = 0, \qquad \nabla \times \boldsymbol{B} = 0.$$



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

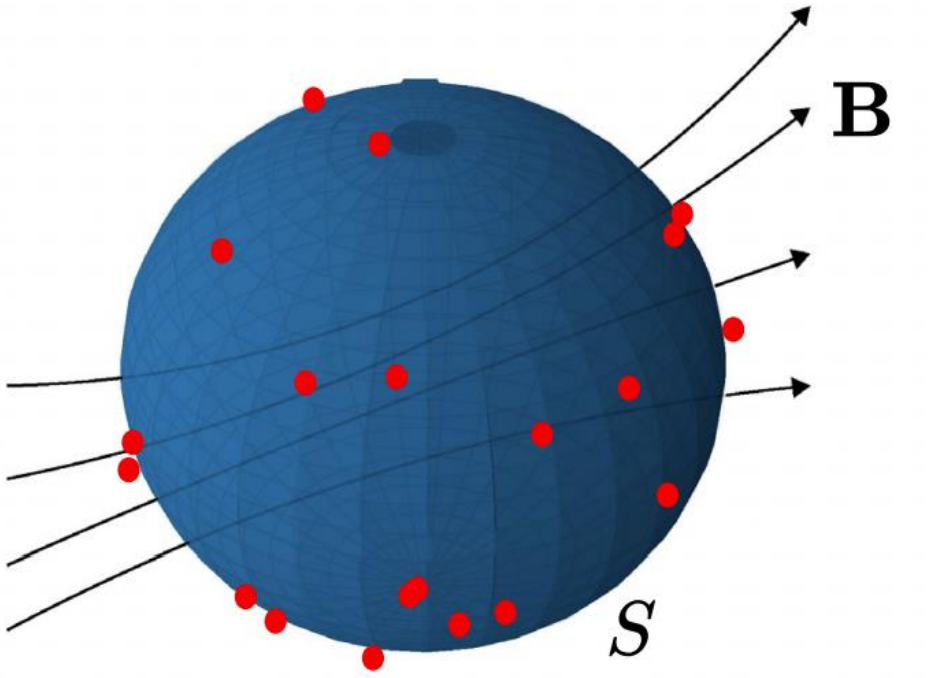
$$\text{Loss}_{\nabla\cdot\boldsymbol{B}} := \frac{1}{N_f} \sum_{i=1}^{N_f} |\nabla \cdot \boldsymbol{B}(\boldsymbol{r}_d^i)|^2$$

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

- Input: position (x,y,z)
- Output: field in (x,y,z)
- Not only satisfy the data constraint but also satisfy the physical constraint

AI-Enhanced Method: PINN

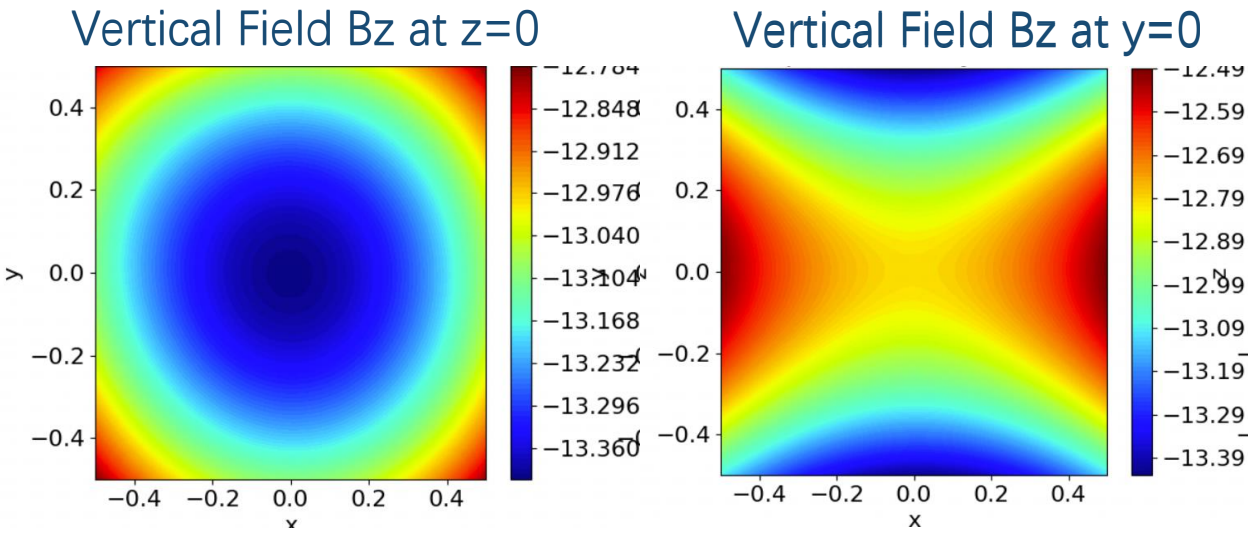
- Select a enclosed surface S and choose some locations on it
- Using the measurements in these locations to predict the inner field
- With enough data points → successfully obtain the true solution (within uncertainty)



- Input: position (x, y, z)
- Output: field in (x, y, z)
- Not only satisfy the data constraint but also satisfy the physical constraint

Simulate the Field: Case 1 (Coils along 1 axes)

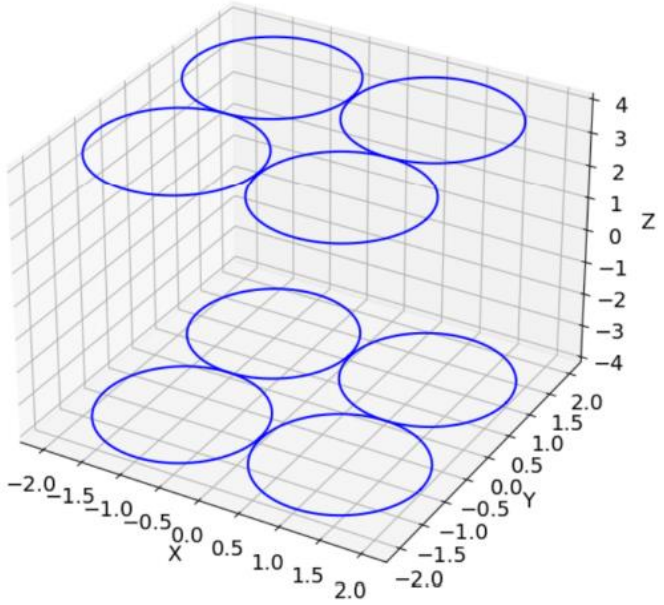
Simulate the magnetic field generated by several current-carrying coils Based on the Biot–Savart law in arbitrary units



$$B_x = C\frac{xz}{2\alpha^2\rho^2\beta}\left[(a^2+r^2)E(k^2)-\alpha^2K(k^2)\right]$$

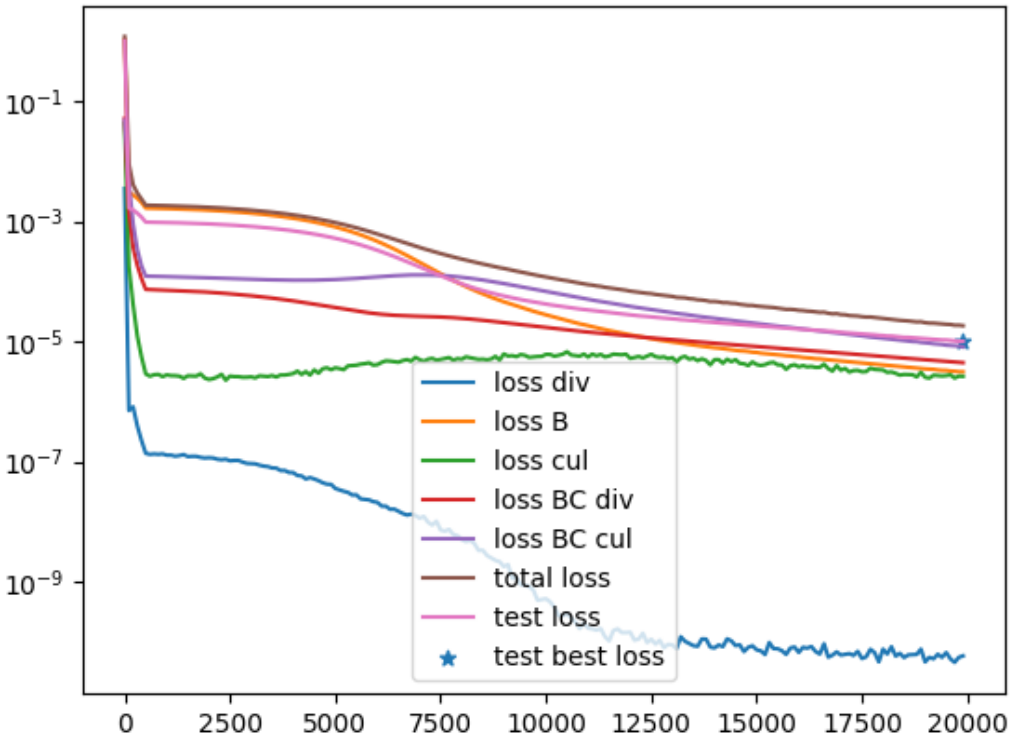
$$B_y = \frac{y}{x}B_x$$

$$B_z = C\frac{1}{2\alpha^2\beta}\left[(a^2-r^2)E(k^2)+\alpha^2K(k^2)\right]$$

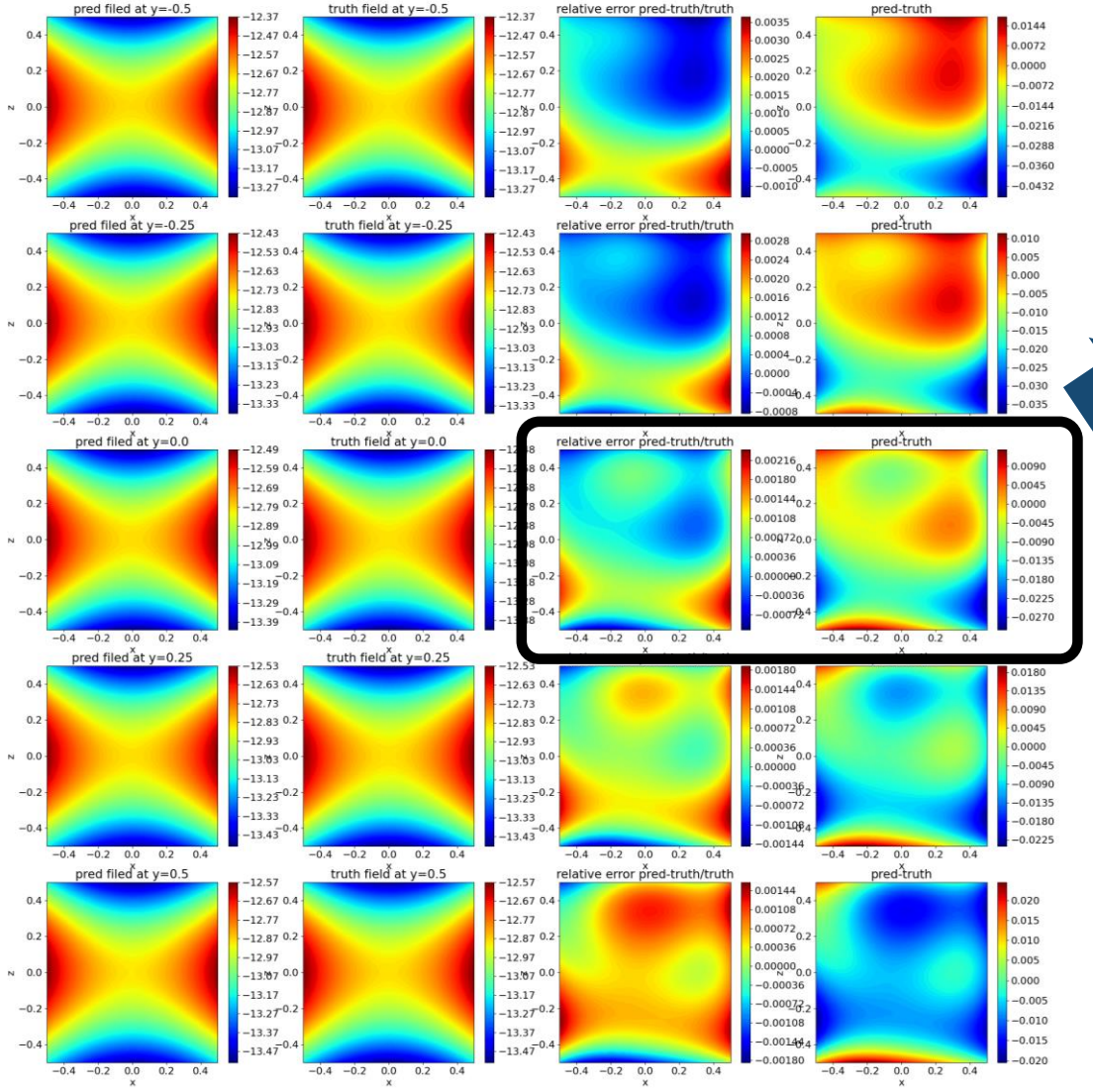


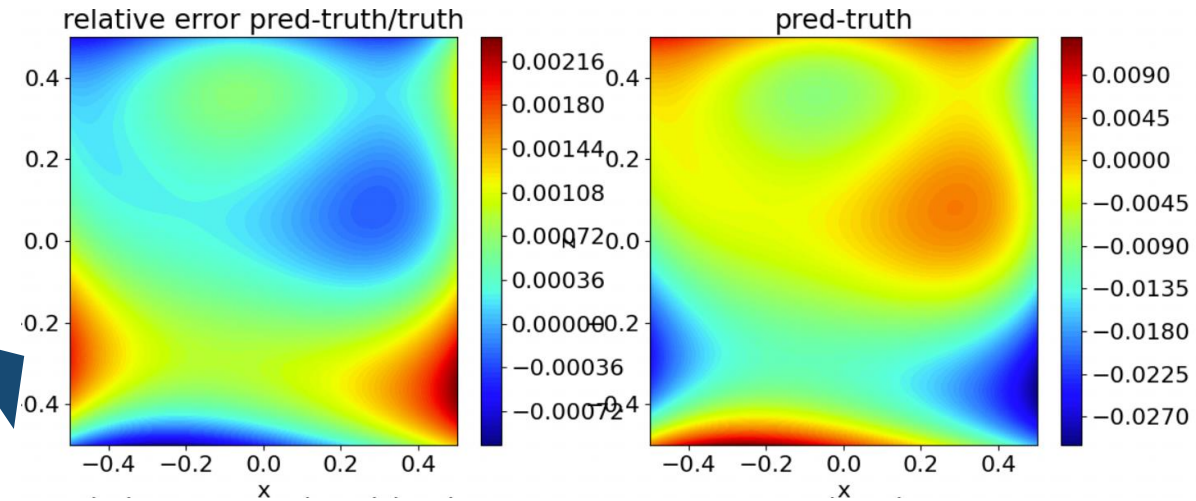
Train the PINN

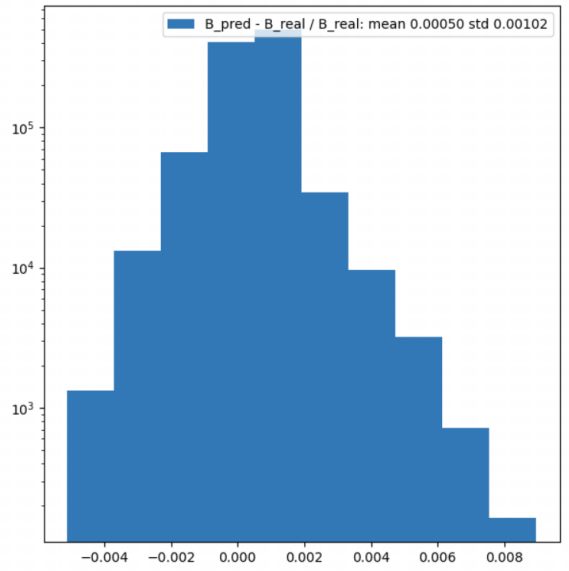
- Select a box region with side length L=1 in arbitrary units
- Predict the field inside the box using the field data on the surface
- Randomly select 18 points on the surface



Prediction Result







Mean relative error ~ 10^{-4}
Std relative error ~ 10^{-3}
(10^6 test data points)

prediction truth (pred-truth)/truth pred-truth

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Simulate the Field: Case 2 (Helmholtz Coil)

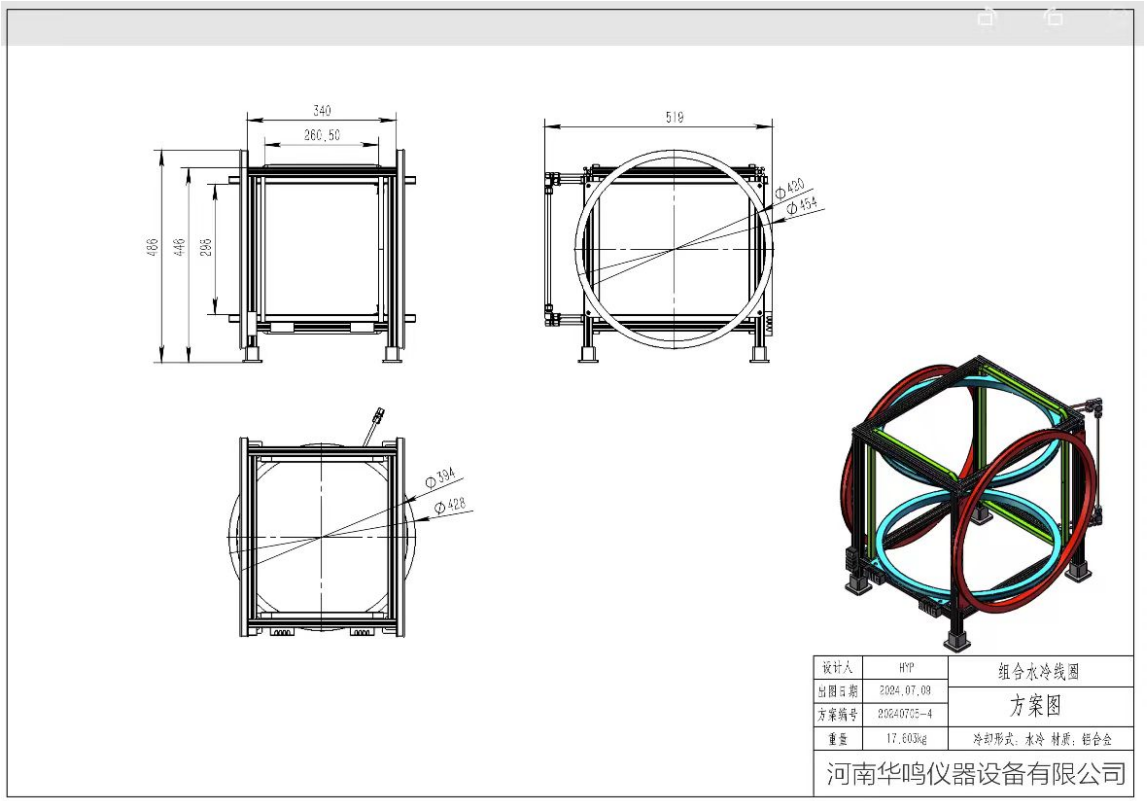
2 circular coils and 1 square coil

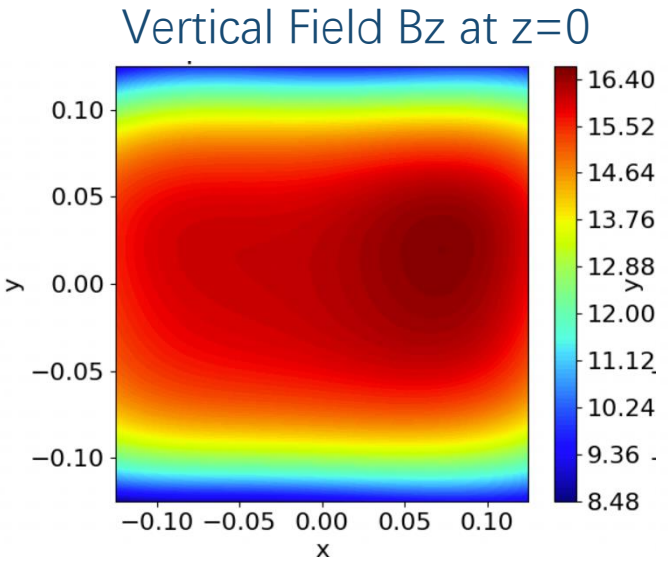
dx	dy	dz	r1	r1	a	b
0.316	0.358	0.358	0.22	0.207	0.378	0.272

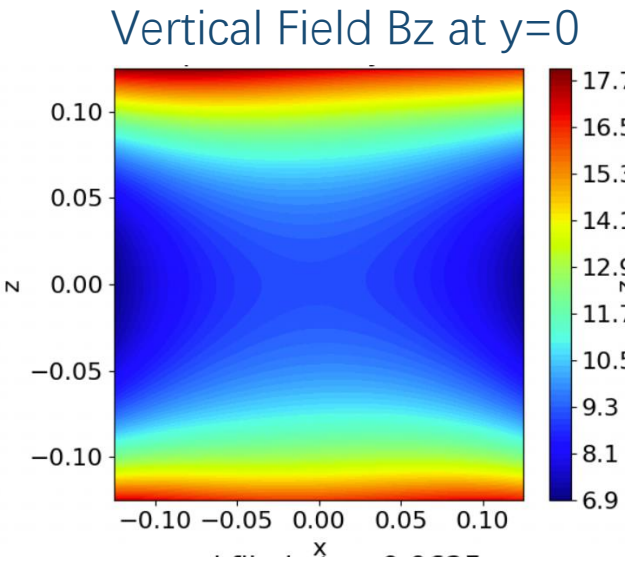
arbitrary units

Ix	Iy	Iz
1	1	5

arbitrary units

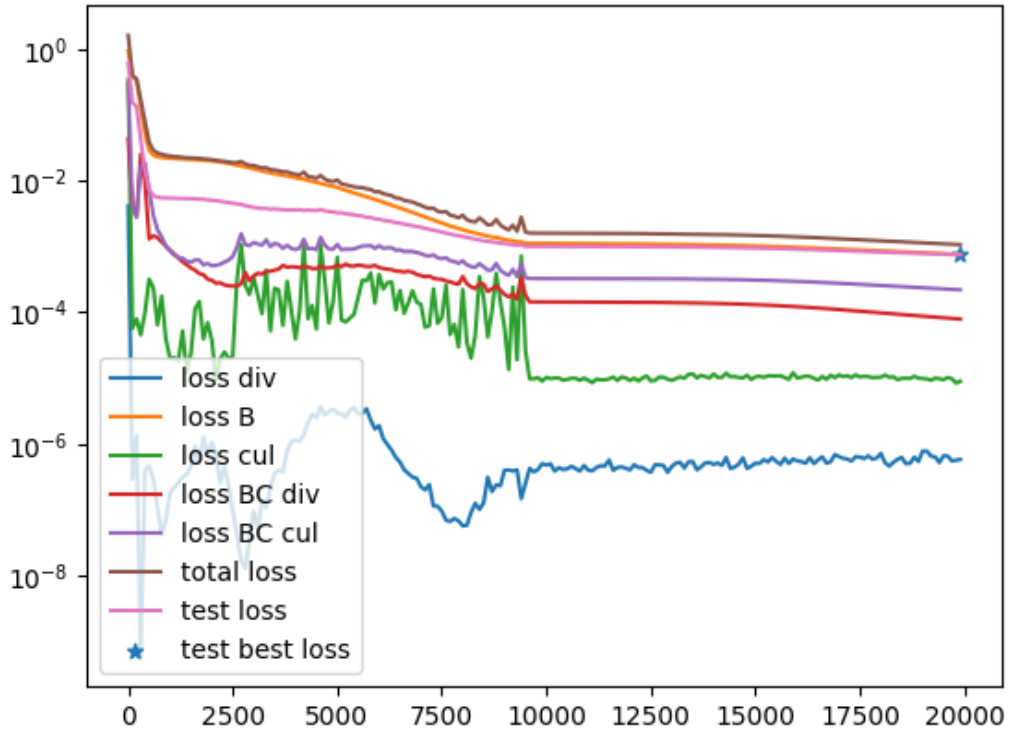




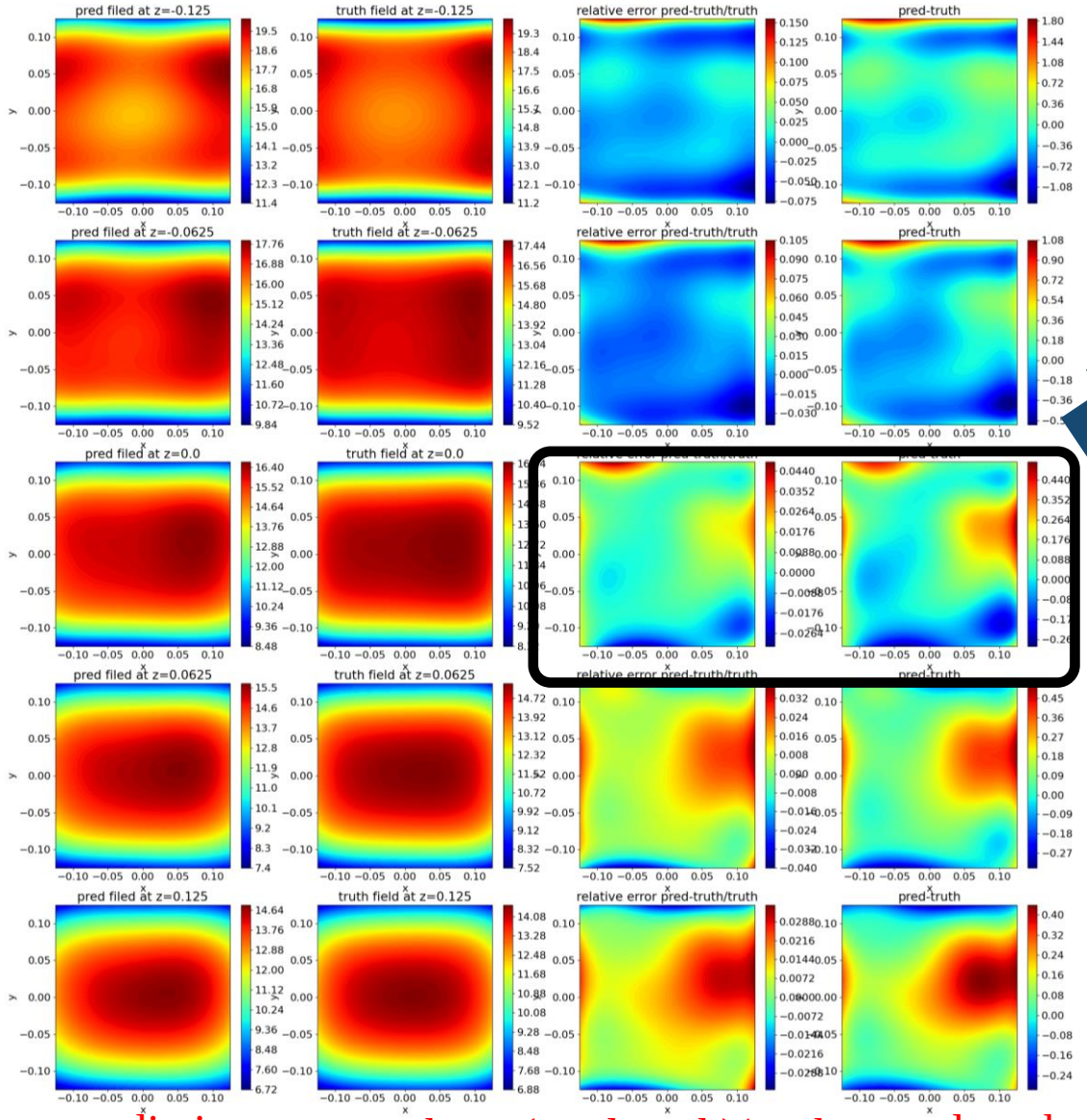


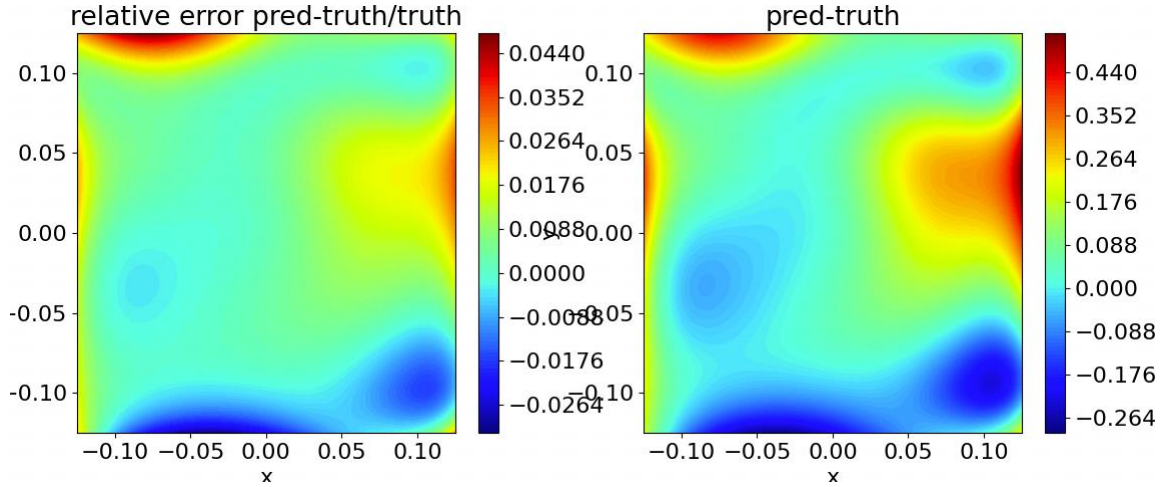
Train the PINN

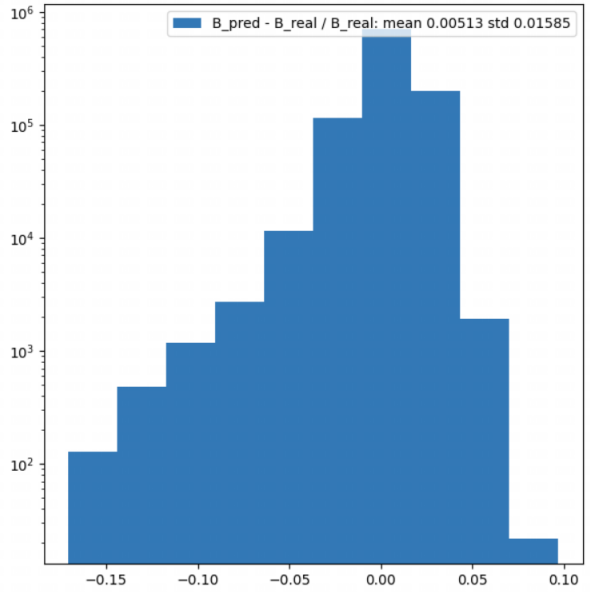
- Select a box region with side length L=0.25 in arbitrary units
- Predict the field inside the box using the field data on the surface
- Randomly select 96 points on the surface



Prediction Result







Mean relative error ~ 10^{-3}
Std relative error ~ 10^{-2}
(10^6 test data points)

prediction truth (pred-truth)/truth pred-truth

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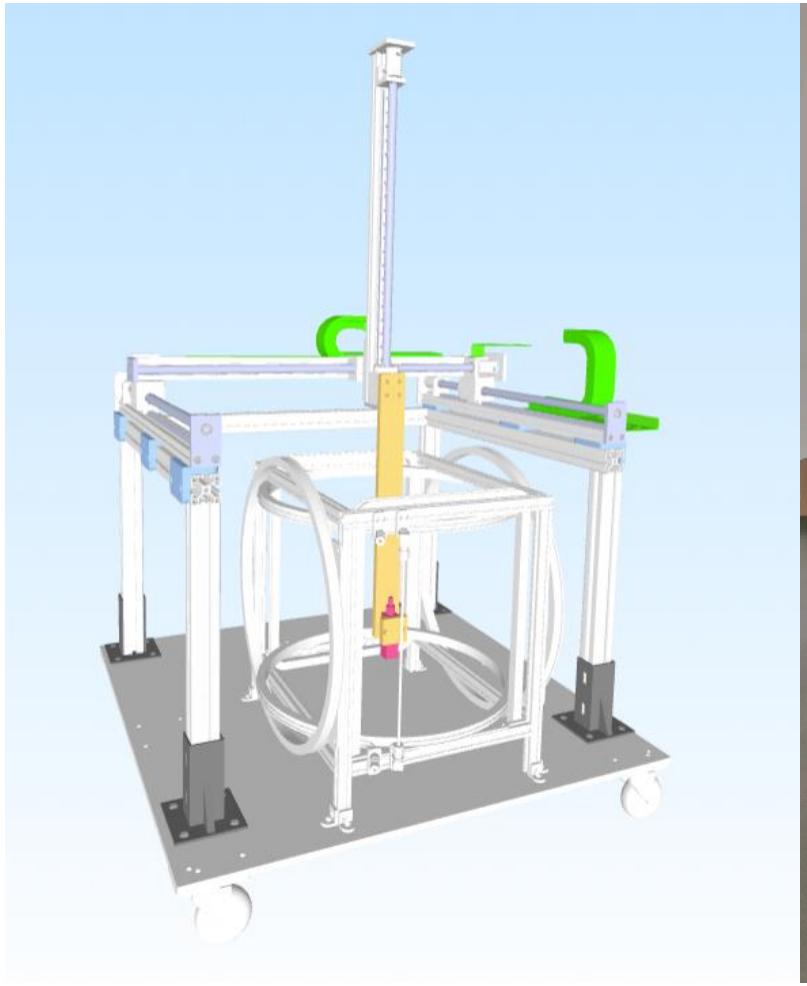
Experimental Data

Helmholtz Coils and Sliding Table System (position resolution ~0.5mm)



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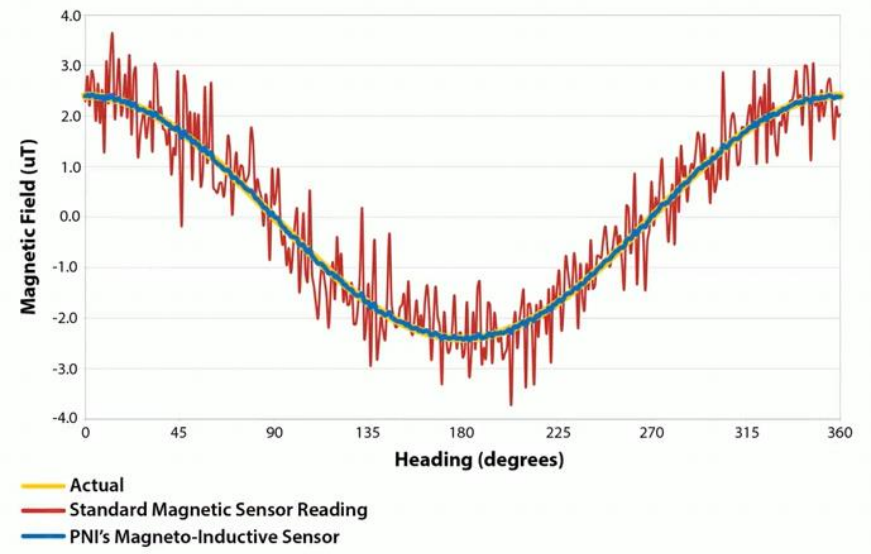
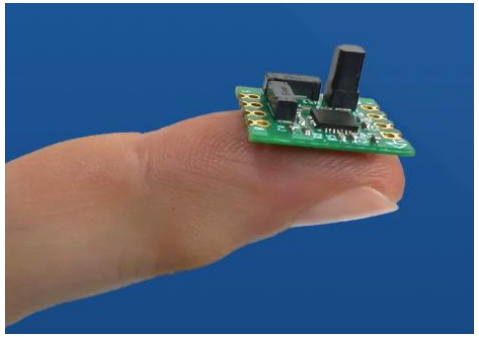
Sensor: RM3100 magneto-inductive sensor

- 23 times better resolution and 33 times less noise compared to traditional Hall-effect sensors
- Core sensors have very small size
- Stable and economic ~ $50



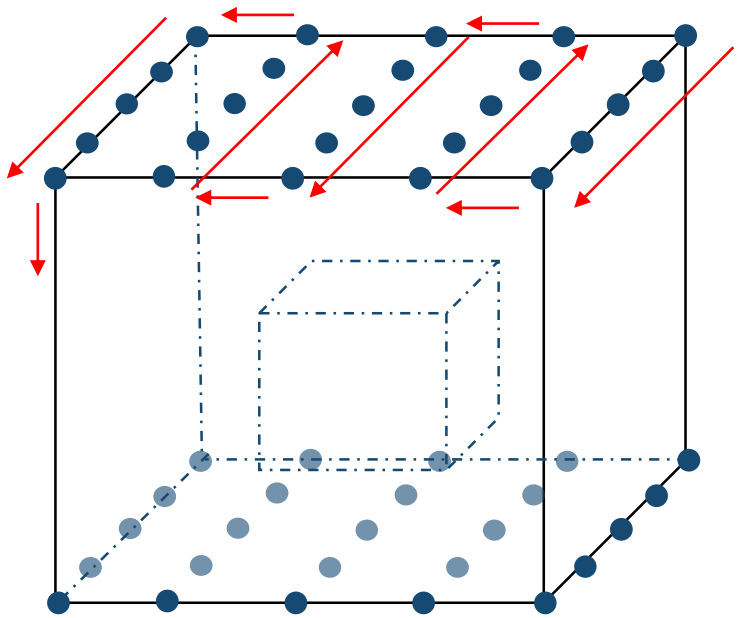


83mm X 25mm X 25mm

Sensitivity	13nT
Noise	15nT
Linearity over +/- 200 uT	0.50%
Field Measurement Range	+/- 1100 uT
Current @ 8Hz, 3 Axes	260 uA
Interface	SPI and I2C
Operating Temperature	-40°C to +85°C

Data Collection

- Adjust the currents of the coils to cancel the geomagnetic at the center point
- The zero-field point is set as the origin point
- Scan a cube region in range [-80mm to 80mm] for each axis with 40mm interval
- At each point, stay 10s to get stable measurements (std ~ 0.03 μT)
- In total collect 125 (5×5×5) points for one loop
- The surface points are used as train data (96 points)
- The inner points are used as test data (27 points)



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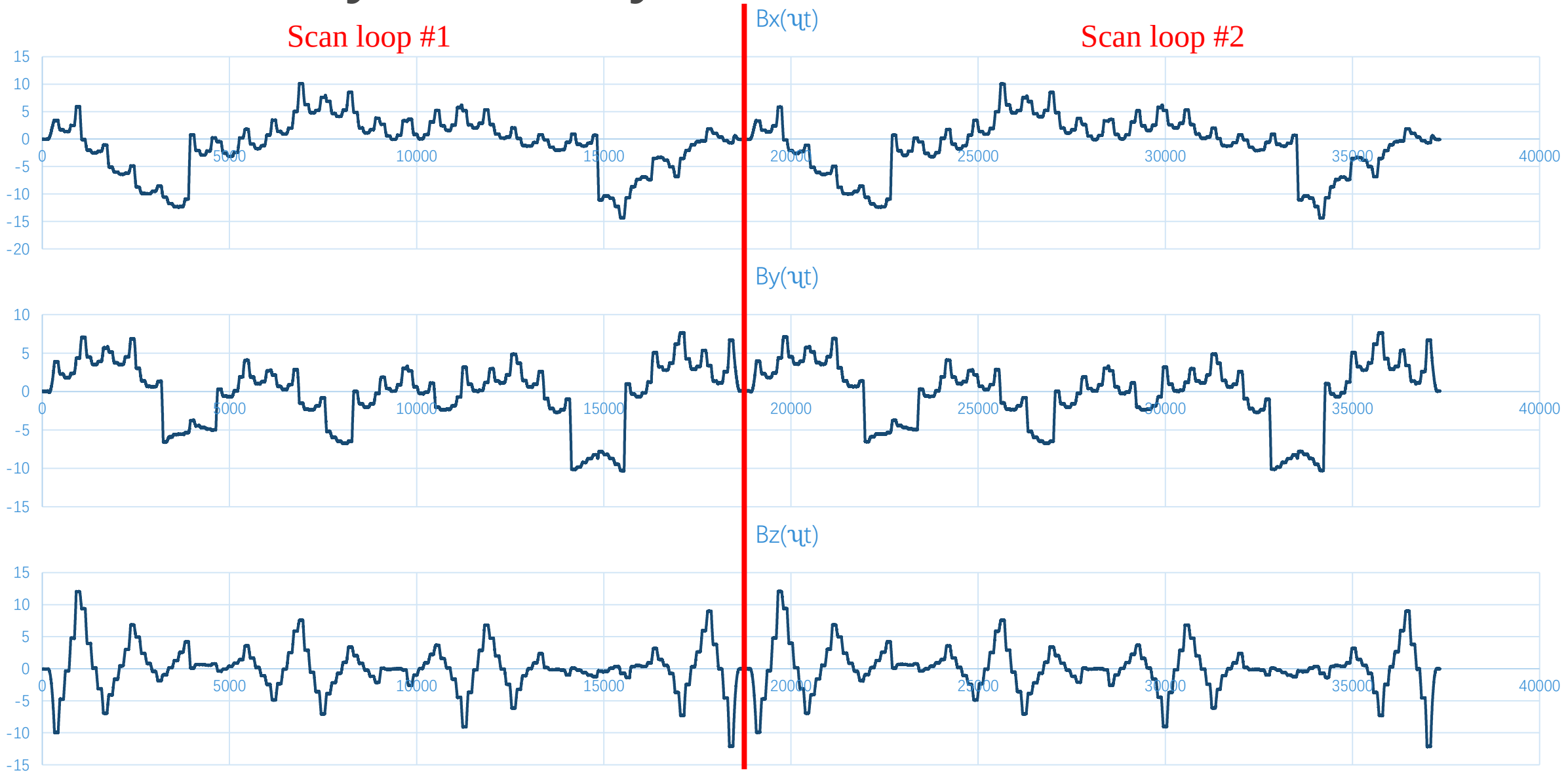
Preliminary Data Analysis



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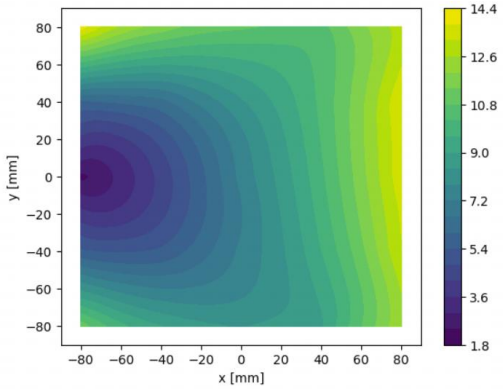
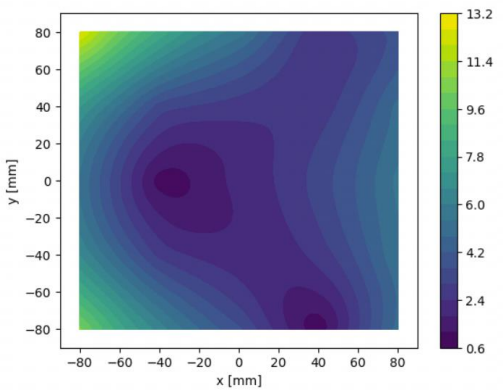
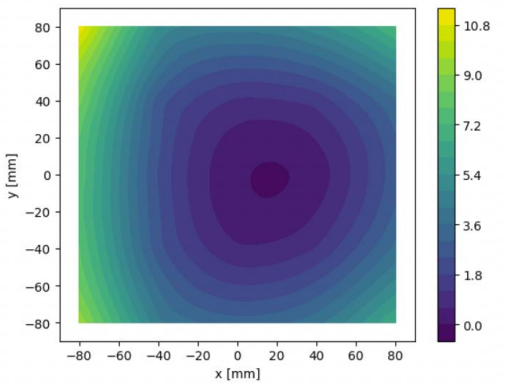
Preliminary Data Analysis



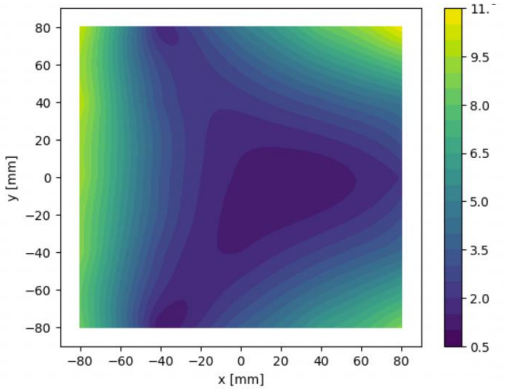
|B| at z=-80



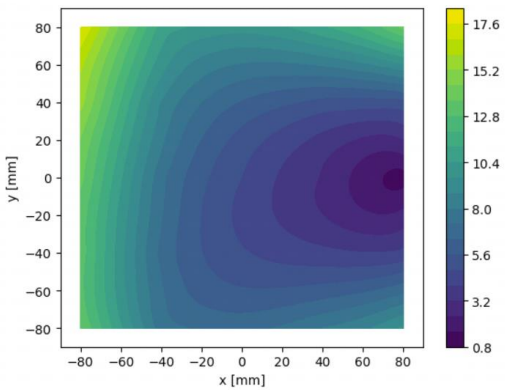
|B| at z=-40



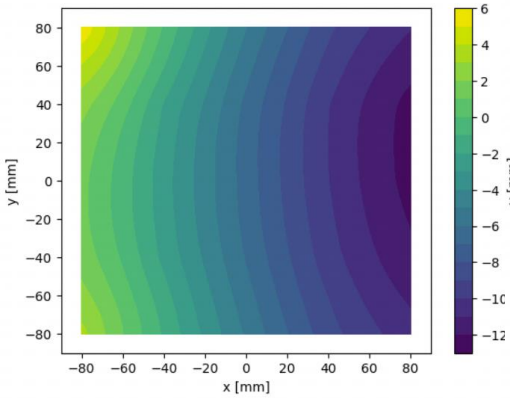
|B| at z=0



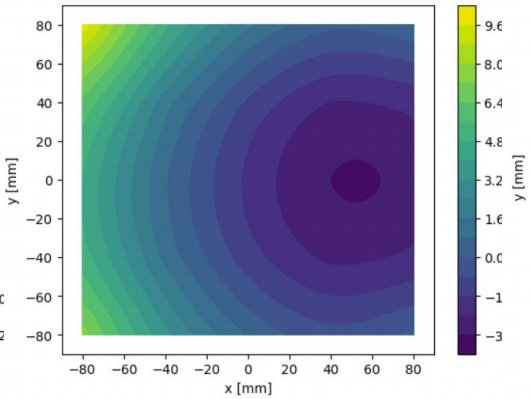
|B| at z=40



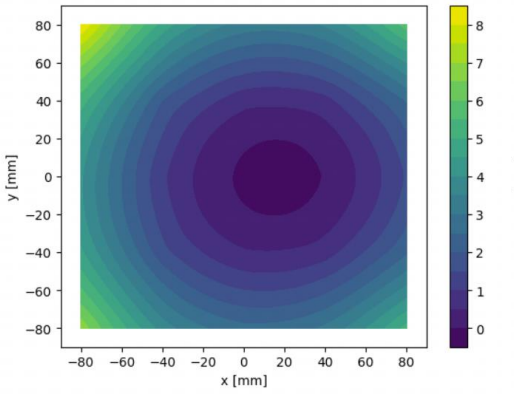
|B| at z=-80



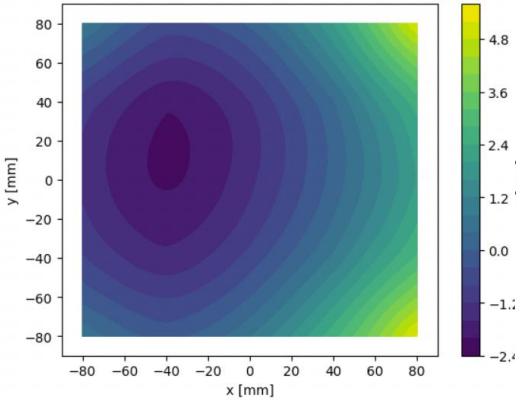
Bz at z=-80



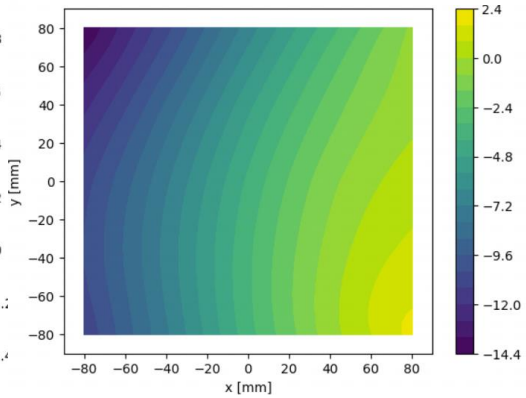
Bz at z=-40



Bz at z=0



Bz at z=40

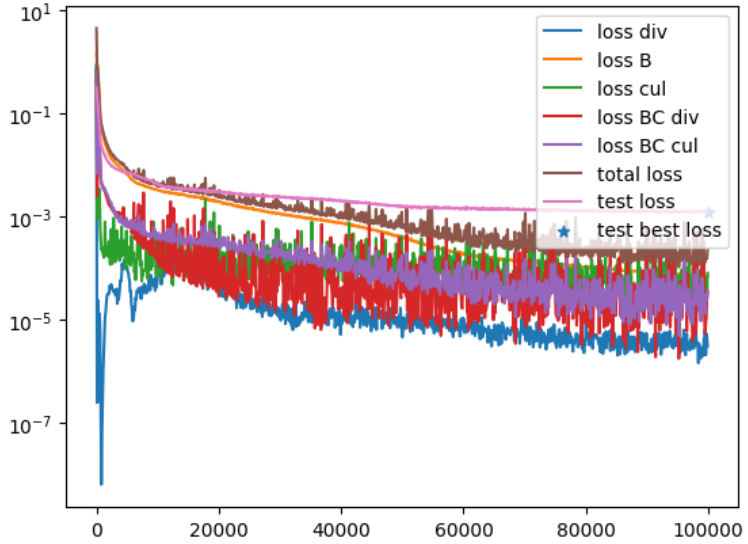


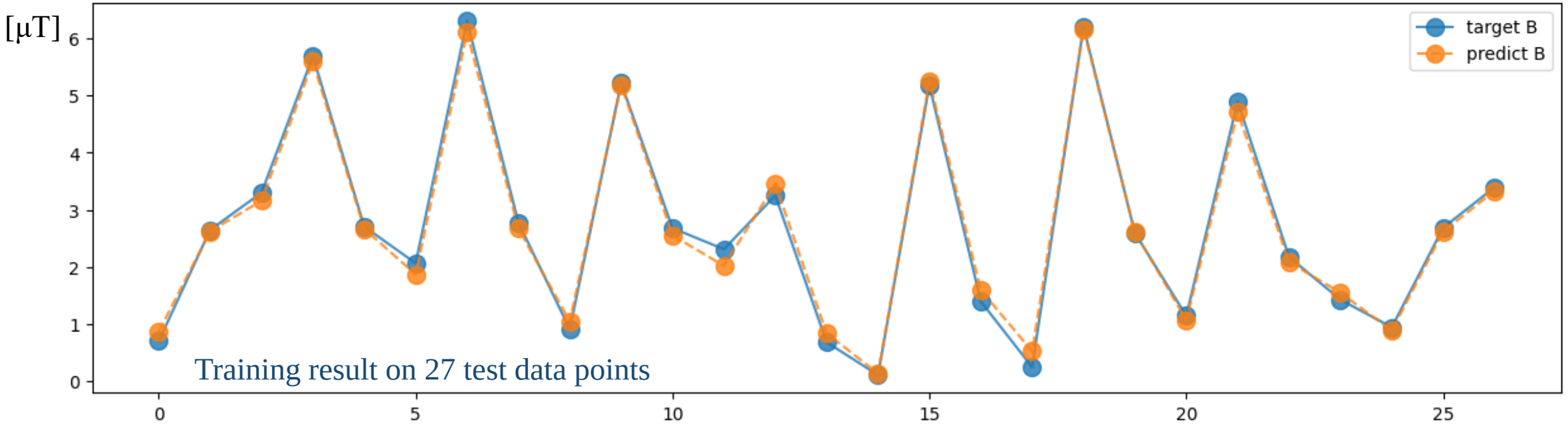
Bz at z=-80

Preliminary Data Analysis

Training Steps：

1. Using the points at the surface as the input training dataset (in total 98 points)
2. The inner 27 points are treated as test dataset
3. Training for 100,000 epochs, the trend of the loss plot is quite similar to the previous result



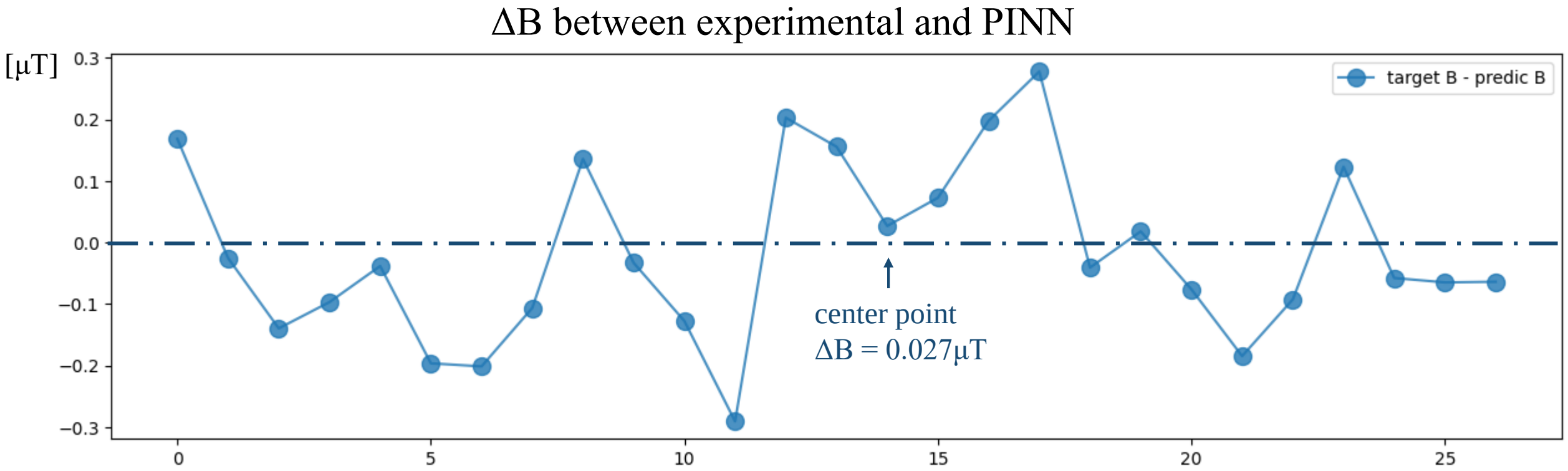


Training result on 27 test data points

之江实验室 ZHEJIANG LAB

Preliminary Data Analysis

- The Mean difference between the test experimental data and the PINN predicted result is ~0.02 μT
- The std is ~0.1 μT
- Both below the magnetic field requirement at the muon production region (±1 μT)



Summary

- Precision magnetic filed measurement is an important part of the muon g-2 experiment
- We develop a AI-Enhanced magnetic field measurements method
- The PINN can both optimize the neural network from the data and the physics constrains
- We built a coil and sliding table system to collect the real magnetic field data
- A suitable fluxgate sensor which can monitor the tiny field in high precisions
- The PINN method in experimental data shows promising result

Outlook

- ML for PDE remain a laboratory product, performing better in simulated data but facing many challenges with real-world data
- The PINN can be further improved by applying advanced optimization and better data taking/preprocessing
- We plan to try more physical informed AI method like DeepONet / FNO

Questions or comments are very welcome!