

# Consideration on application of neural networks to realize 3D beam injection

3次元らせんビーム入射の実現に向けた  
機械学習 Neural network の活用検討

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@ 4th Acc ML workshop

# Abstract

- For a precise muon g-2 measurement in J-PARC, we want to store relativistic muon in a compact ring.  
To realize this, a new injection scheme, called “3D beam injection”, is being developed.
- Design method for this non-standard optics must be developed.
  - consideration on performance (injection efficiency), robustness of the design, and commissioning strategy.
- The beam optics of 3D injection has specific features:
  - Strong focusing: skew component of fringe field ( $f \sim 0.03m$ ) + Drift length ( $L \sim 30m$ )
  - Intrinsic non-linearity: Non-linear B-field distribution, Small radius effect
- Conventional tool to tackle this system is Lie map and truncated polynomials. Representing it by neural network may give us a guideline for beamline design.

This is still an “idea phase”. Any suggestions from experts are very welcome.

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2. Beam optics of 3D injection
  - Difficulty in its design and its realization
3. Utilization of neural network
4. Summary

# Muon g-2 measurement in a compact ring

- Muon g-2 is a powerful tool to validate possible contribution from BSM.
  - (in my opinion) the situation on muon g-2 is “ambiguous”
    - Measurement of ee->had cross section is inconsistent with lattice QCD calculation.
    - Additional data from experimental side is needed.
- Previous experiments (at CERN/ BNL/FNAL) : “magic-γ approach”
 
$$\vec{\omega}_a + \vec{\omega}_\eta = -\frac{e}{m_\mu} \left[ a_\mu \vec{B} - \left( a_\mu - \frac{1}{\gamma^2 - 1} \right) \frac{\vec{\beta} \times \vec{E}}{c} + \frac{\eta}{2} \left( \vec{\beta} \times \vec{B} + \frac{\vec{E}}{c} \right) \right]$$

= 0 at  $\gamma=29.3$ ,  $P=3.1\text{GeV}/c$
- New experiment at J-PARC : “zero E-field approach”
 
$$\vec{\omega}_a + \vec{\omega}_\eta = -\frac{e}{m_\mu} \left[ a_\mu \vec{B} - \left( a_\mu - \frac{1}{\gamma^2 - 1} \right) \frac{\vec{\beta} \times \vec{E}}{c} + \frac{\eta}{2} \left( \vec{\beta} \times \vec{B} + \frac{\vec{E}}{c} \right) \right]$$

= 0 at  $\vec{E}=0$

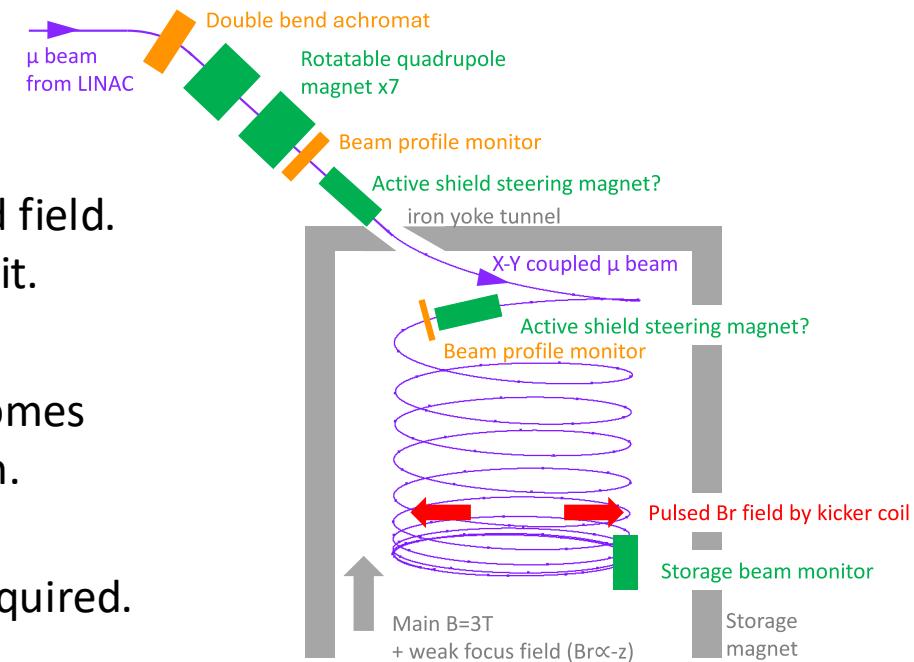
  - Key concept: Measurement of lower muon momentum with more compact setup.
- Injection of relativistic beam into small radius ring is needed.
  - Muon beam of 300 MeV/c ( $\gamma=3.0$ ), Ring radius  $r = 0.33\text{m}$  at  $B = 3.0\text{T}$ .
- We need to store almost all the muons in the “good field region”.
  - The experiment relies on the uniformity of B-field where muon is stored.

# How we can inject beam into compact ring?

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- The conventional beam injection scheme will not work.  
Too fast and too strong kicker system is demanded.
  - Smaller cyclotron period requires fast kicker pulse.
  - Smaller radius requires larger kick angle  
= (septum thickness/ring radius).
  - In our case, a kick of  $BL \sim 30$  mT in 7 ns is needed.  
This is out of technical reach.

- We are developing a new injection scheme, called “3D beam injection”.
  - Beam follows helical orbit by solenoid field.  
Kicker field is gradually applied along it.
  - Advantage: Required kicker field becomes within the technical reach.
  - Challenges: Precise beam control in a complicated optics is required.



# What we want to achieve

## Goal

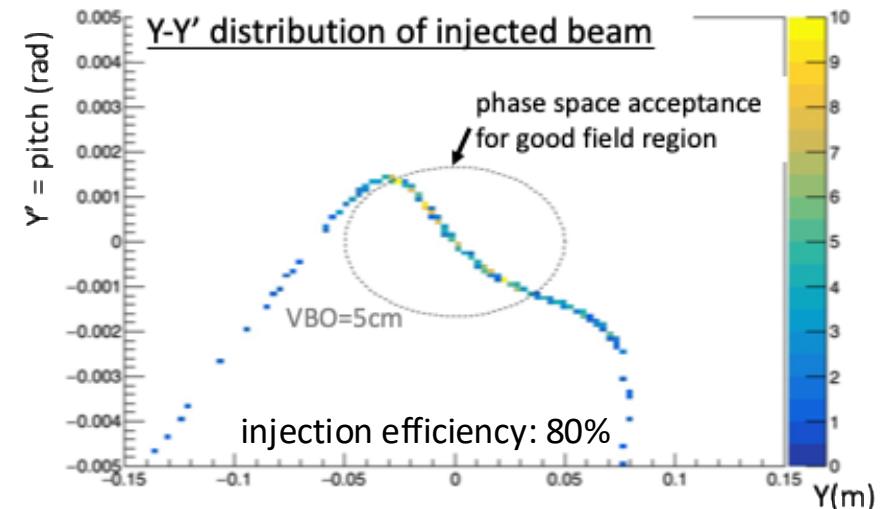
- We need to design this injection system having
  - high injection efficiency ( $>80\%$ )
  - sufficient robustness for the error on B-field and incoming beam
  - realistic commissioning plan (B-field probe, beam monitor, tuning knob)

## Method

- Design method for this non-standard optics must be developed.
  - It looks like much different from the standard beamlines,  
the framework of beam dynamics should be still applicable and useful.

## Status

- A configuration which achieves 80% injection efficiency was found.
  - Based on the linear optics approximation of this system.
  - non-linear effect is observed.



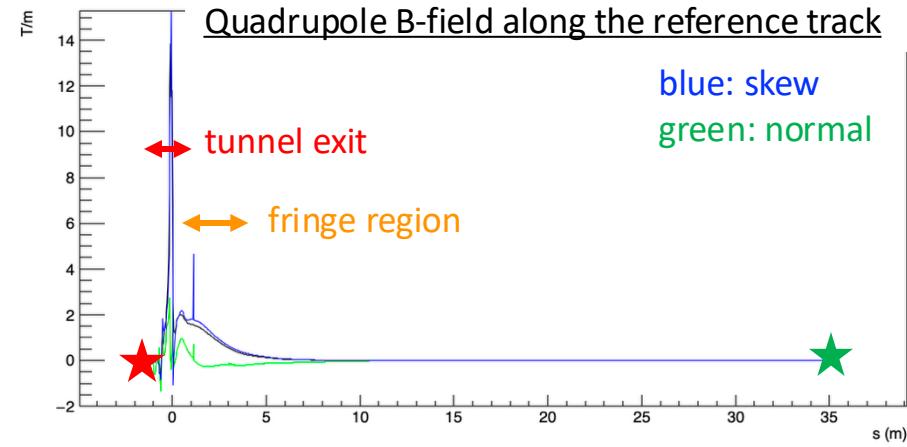
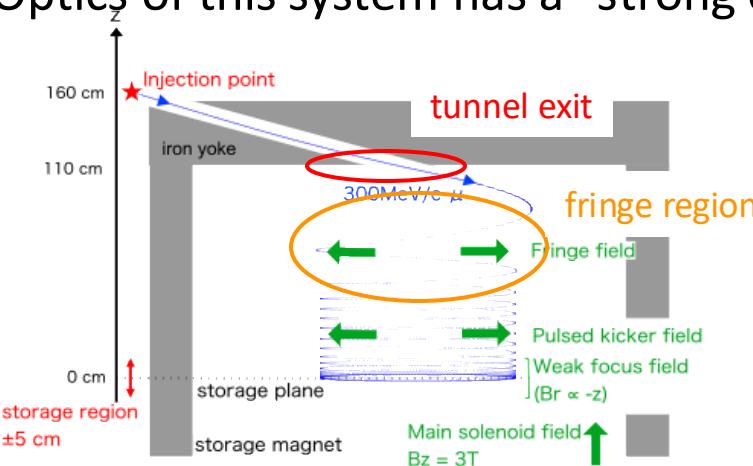
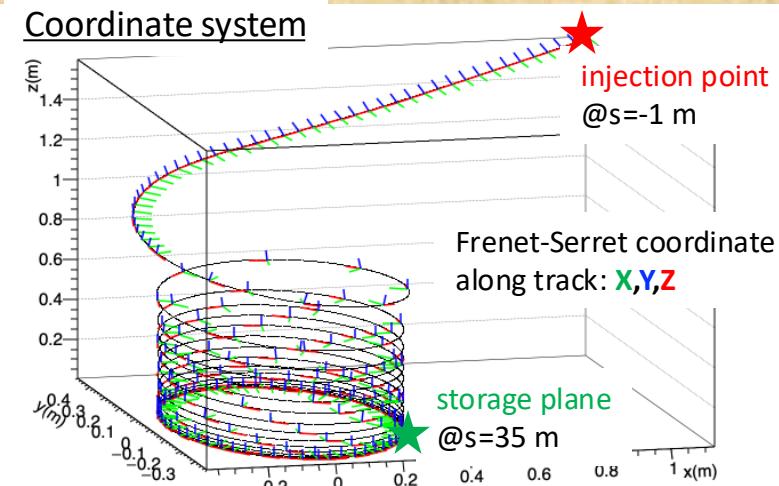
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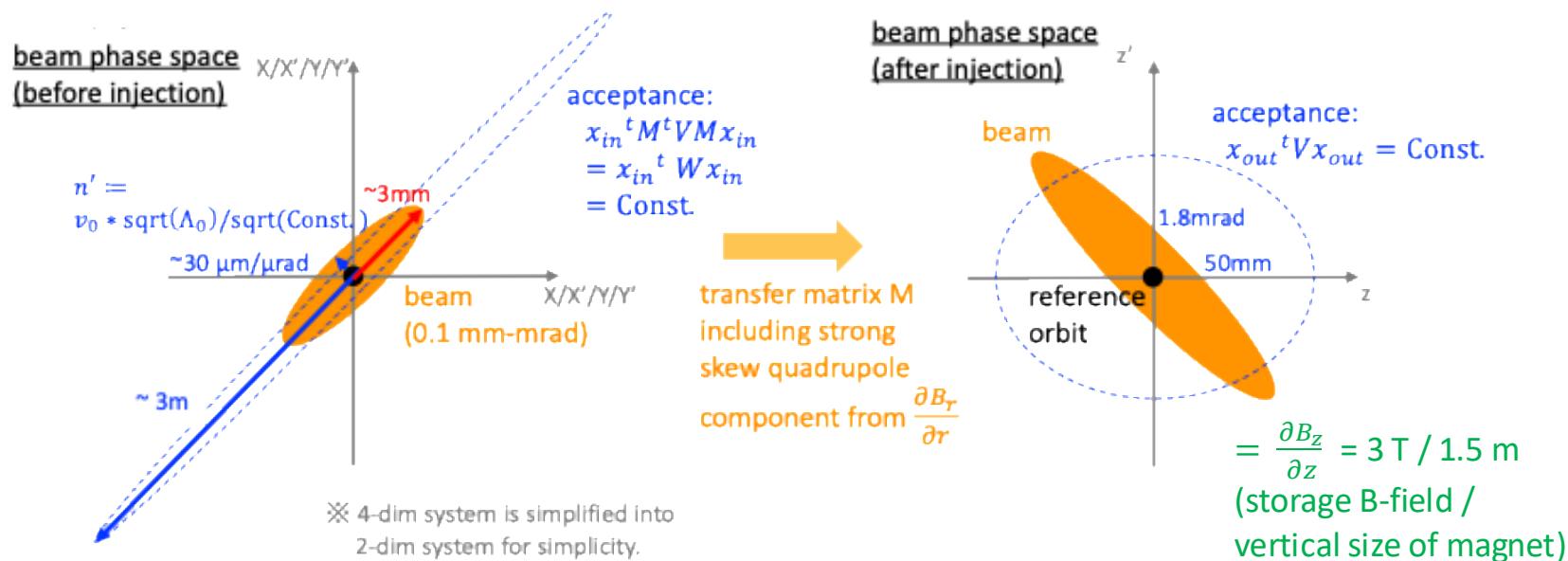
# Feature of 3D injection: “strong defocusing with XY-coupled way” 8

- Frenet-Serret coordinate is defined along the reference track to treat this in beam dynamics.
- The beam feels strong skew quadrupole field by the fringe of 3T storage magnet.  $\rightarrow$  focal length of 3cm for X-Y coupled way  $\ast$
- It is followed by drift length of  $\sim 30$ m before reaching the storage plane.
- Optics of this system has a “strong defocusing effect with XY-coupled way”



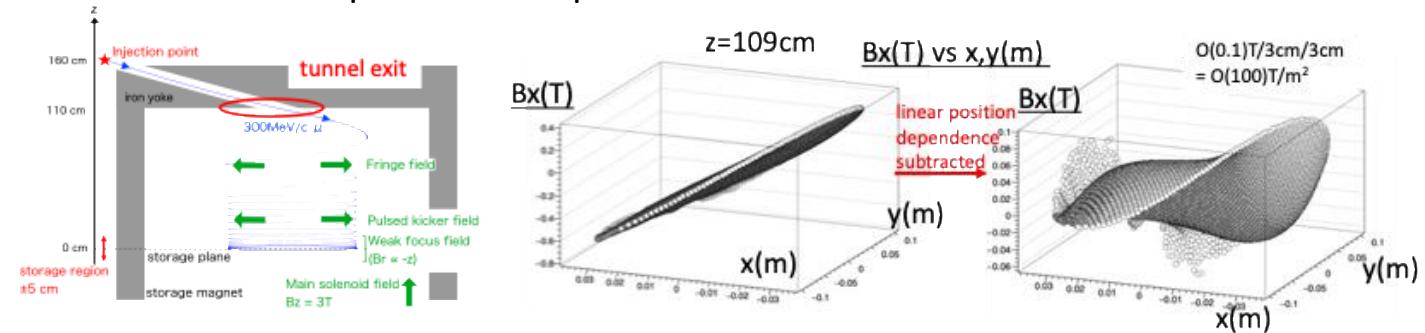
$\ast$  In addition, longitudinal field ( $Bz$ ) also contributes X-Y coupling.

- The strong skew quadrupole field is inevitable.
  - $\frac{\partial B_r}{\partial r}$  at finite radius is induced from  $\frac{\partial B_z}{\partial z}$ , as we inject beam from  $B_z = 0$  T to  $B_z = 3$  T.
- Due to this strong defocusing effect, a tiny shift of the injecting beam is magnified to a large shift.
  - magnification factor: 1000 (= “drift length  $\sim 30$ m”/“focal length  $\sim 3$ cm”)
- This requires us a precise beam control at the injection point in 4-dimensional beam phase space( $X, X', Y, Y'$ ).
  - This is achieved by beam transport line having XY-coupled optics (rotated Q-mags).



# Intrinsic non-linearity

- Additionally, inevitable non-linearity effect can happen.
  - some of them can be enhanced by magnification term in linear optics.
- Source of non-linearity No.1 : **Non-linear positional dependence of B-field**
  - B-field around tunnel region has strong positional dependence, including non-linearity
  - Kicker field also has non-linear positional dependence



- Source of non-linearity No.2 : **Small ring effect**
  - Our compact ring setup may make the “small ring effect” non-negligible.

$$H(x, y, z, \tilde{p}_x, \tilde{p}_y, \delta; s) = - \left( 1 + \frac{x}{\rho} \right) \left[ (1 + \delta) - \frac{\tilde{p}_x^2 + \tilde{p}_y^2}{2(1 + \delta)} + \tilde{A} \right]$$

= “beam size  $\sim 1 \text{ cm}$ ” / “radius  $\sim 33 \text{ cm}$ ” = 0.03

- We need to build a robust system to these non-linearity.
- Hopefully, we may improve the injection efficiency by correcting them.

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# Conventional tool to tackle this system

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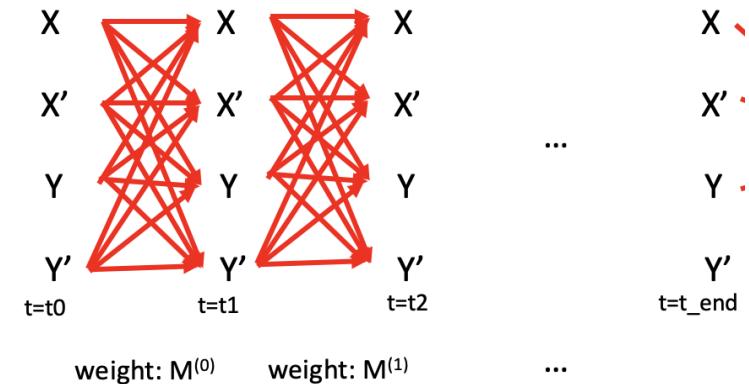
- Conventional tool to treat non-linear beam optics is “Lie map”.
- Time evolution of phase space parameters under Hamiltonian  $H$ :  
$$\frac{dx}{ds} = -[H, x], \text{ where } [A, B] \equiv \frac{\partial A}{\partial q} \frac{\partial B}{\partial p} - \frac{\partial B}{\partial p} \frac{\partial A}{\partial q}$$
- The transfer map  $\mathcal{M}$  ( $x(s = ds) = \mathcal{M} x(s = 0)$ ) from one point to another point along the beamline can be evaluated as:
  - $\mathcal{M} = \exp(-ds; H)$ ,where  $:A:B \equiv [A, B]$ ,  $\exp(-ds; H) \equiv \sum_{k=0}^{\infty} \frac{(-ds)^k}{k!} (:H:)^k$
- Thus, once the B-field is given,  $H$  is determined, then  $\exp(H)$  can be calculated.
- In the computation, the infinite series is truncated at some dimension.

→ Transfer map is represented by truncated polynomials or tensor map.

# Neural network as a transfer map

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- Representing this Lie map by neural network is a recently proposed topic.
  - Time evolution of each step is represented as a map between layers.
    - For example, for the linear optics  $x_{out} = \prod_l M^{(l)} x_{in}$ , the weight of the network  $w_{ij}^{(l)}$  is transfer matrix of each step  $w_{ij}^{(l)} = M_{ij}^{(l)}$ .
    - Non-linear term can also be added, of course.
- This is a physically interpretable network, and a new representation of the Lie map.
- Previous works utilized this representation for beam optics correction in real machines.
  - Polynomial Neural Networks [1]
    - Implement taylor map as neural network.
    - Utilized in PETRA in DESY.
  - Deep Lie Map Network [2]
    - Implement Lie map as neural network.
    - Utilized in SIS18 in GSI



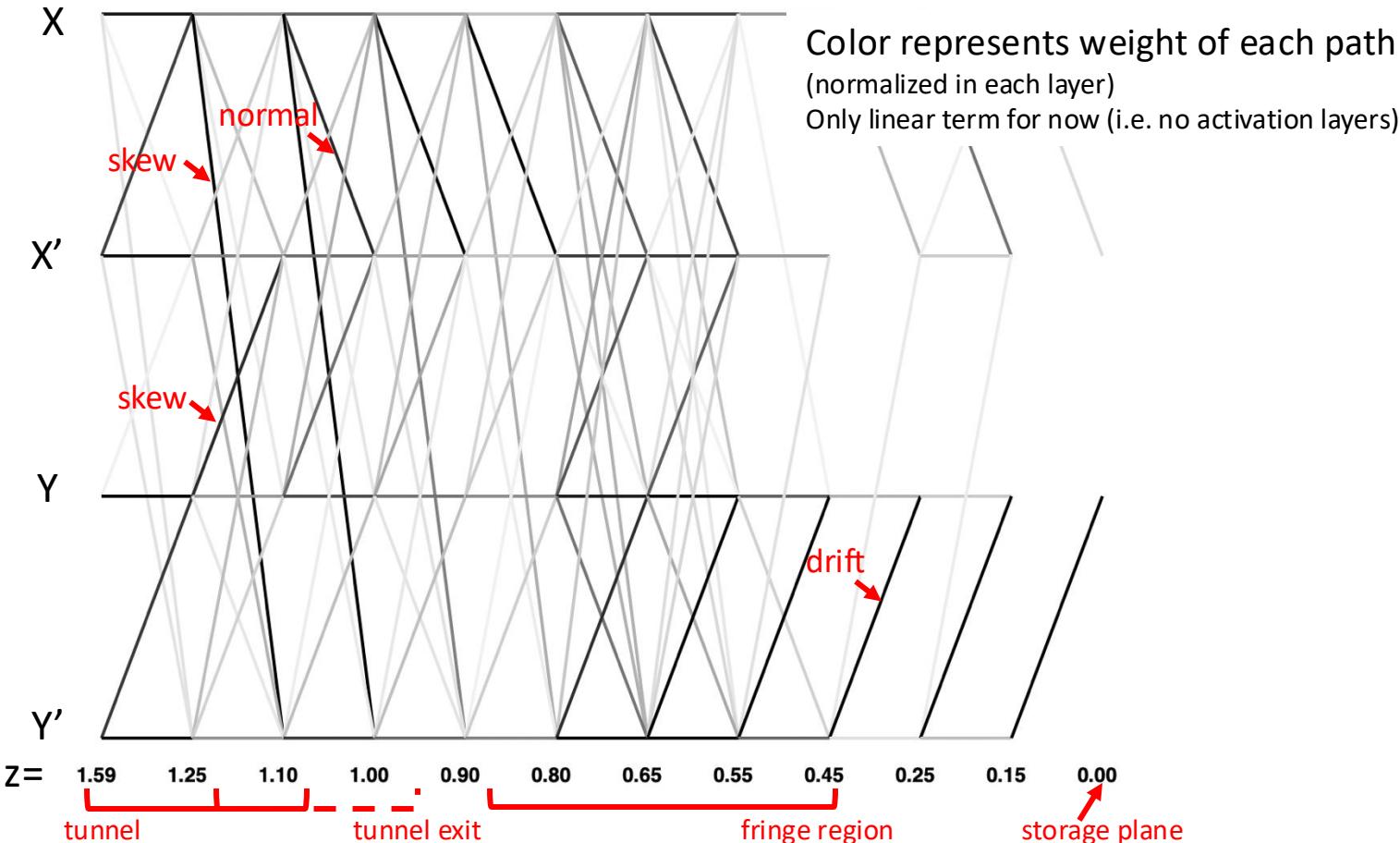
[1] Ivanov Andrei and Agapov Ilya, Phys. Rev. Accel. Beams, 23, 074601 (2020)

[2] Caliari Conrad and Oeftiger Adrian and Boine-Frankenheim Oliver, Phys. Rev. Accel. Beams, 28, 024601(2025)

# Neural network as a transfer map

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- Representation of 3D injection optics. (only linear term for now)



- (Though this is not an essential benefit, but technically)  
This gives us a graphical intuition on our optics  
than a series of the transfer matrix.

This representation of the Lie map by neural network seems to have several advantages for the system having complicated optics like 3D injection.

### No.1: Auto-differentiability of the model

- In NN, back propagation gives us  $\frac{\delta(\text{eval. func.})}{\delta(\text{input beam})}, \frac{\delta(\text{eval. func.})}{\delta(\text{weight} \sim \text{B-field})}$ .
- This is the “robustness” and “required precision” of the system.  
-> Basis for beamline design including errors.
- If we add non-linear devices on the transport line, this tells us its optimal configuration.

### No.2: “Learning” in the real commissioning

- Based on the model optics in the design, we can train the model with real data in the commissioning.
  - as is already done in previous works ([1][2] in P.13)
- We may include this as a “default plan” from the beamline design.

# Summary

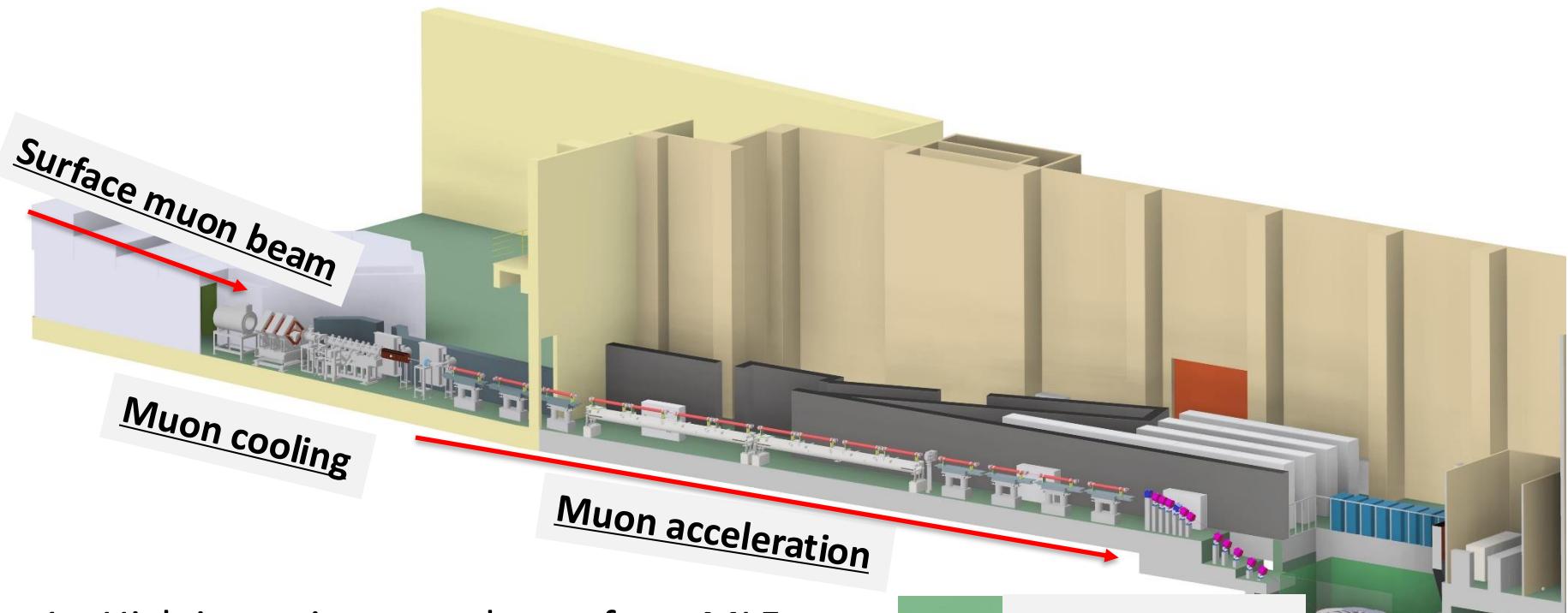
- We would like to store relativistic muons in a compact ring.
- A new 3D beam injection scheme is being developed for this.
- Its beam optics has intrinsic strong defocusing, and intrinsic non-linearity.
- Design method for this non-standard optics must be developed.
- Augmentation of the conventional Lie map for non-linear optics by neural network representation can benefit the design of 3D injection.
  - Especially its auto-differentiability.
- Planned next step is try building a model.
  - B-field map from FEM -> Hamiltonian -> Transfer map neural network  
-> Robustness of the system, Interpretation of the system, beam monitor design, etc...

*Any comments, suggestions are very welcome.*

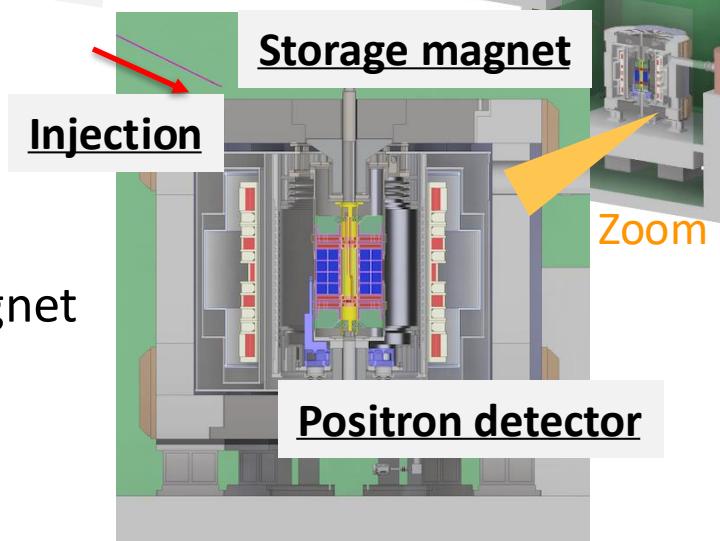
# BACKUP

# Experimental setup overview

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1. High intensity muon beam from MLF
2. Low emittance beam by muon cooling & reacceleration.
3. Dedicated beam injection scheme.
4. Quite uniform B-field by MRI-like magnet
5. Compact detector with high hit rate tolerances



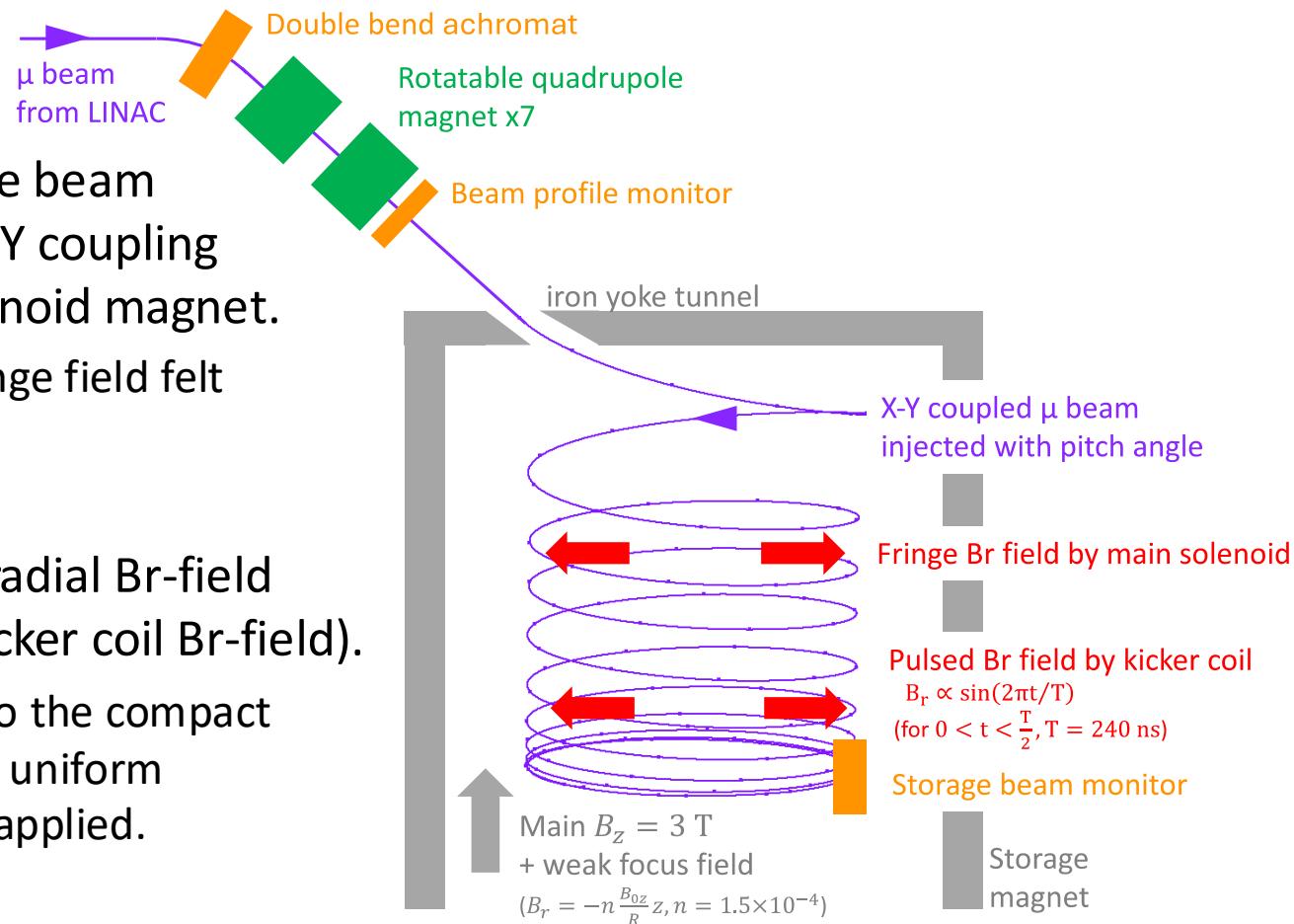
# Three-dimensional spiral beam injection

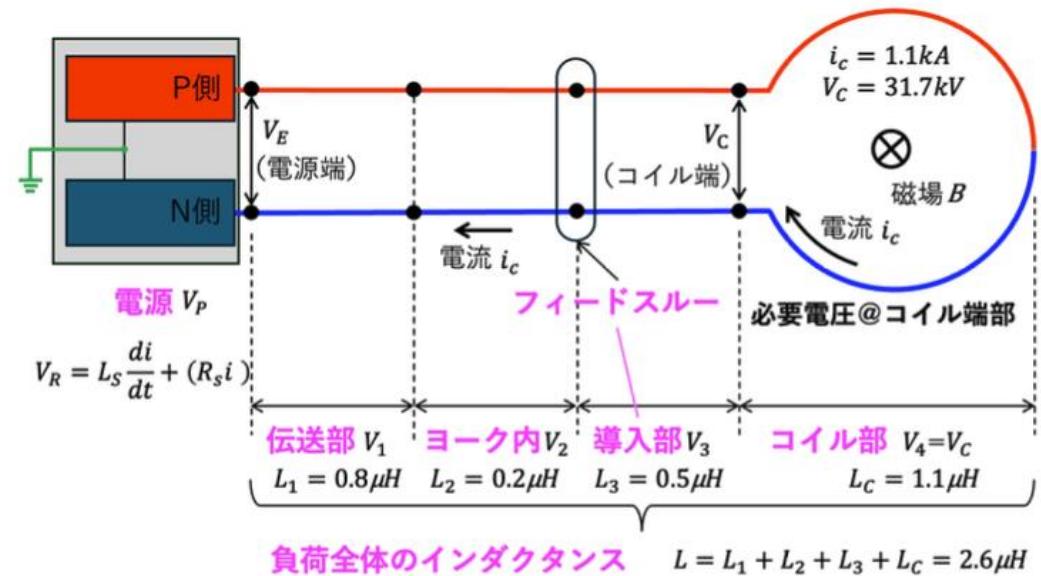
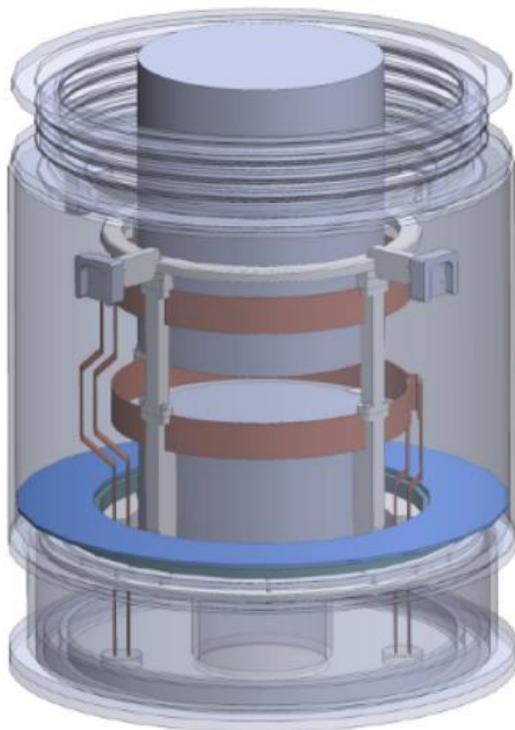
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- Low emittance muon beam (300MeV,  $0.3\pi$  mm-mrad) will be injected into compact storage orbit ( $B_z=3.0\text{T}$ ,  $R=33.3\text{cm}$ ), and stored without electric focusing with good injection efficiency.

## Key points

1. Inject low emittance beam with appropriate X-Y coupling is injected into solenoid magnet.
  - to compensate fringe field felt by each muon
2. Apply appropriate radial Br-field (Fringe Br-field + kicker coil Br-field).
  - to guide muons to the compact region where the uniform magnetic field is applied.
3. Store muon beam by weak focusing.





## A: Clarification of requirement from physics

- What is required from g-2/EDM measurement in compact storage ring?

seems to be world-first  
not world-first, but rare

## B: Design method and overall design of 3D beam injection

- 3D beam injection is a **brand new injection scheme**  
**which includes complicated beam dynamics.**

## C: Kicker system

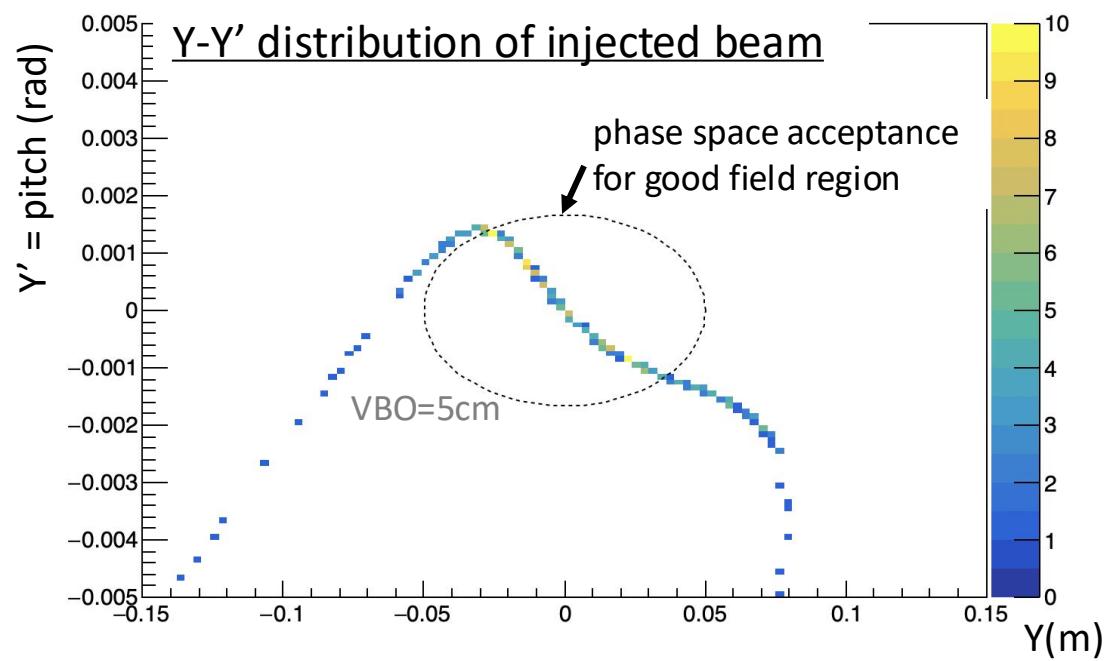
- High power kicker system with **little timing jitter** and **little residual field**

## D: Transport beam line

- Beam orbit and phase distribution control in strongly XY-coupled system

## E: Beam transport inside storage magnet

- Beam orbit and phase distribution control in complicated beam dynamics system



### No.1: Auto-differentiability of the model

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### No.3: Introduction of concepts in neural network

- For our case, it is not clear which effect in the optics is important?  
-> Likely, this can be connected to the “importance of each path in NN”.