Machine learning for QCD global analysis

PI meeting

CENTER *for* NUCLEAR FEMTOGRAPHY

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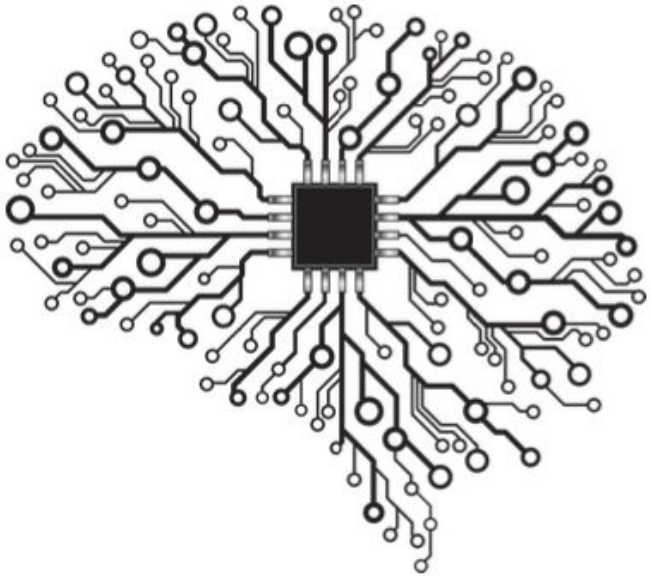
Research: QCD structure of hadrons and nuclei

Outline

Part 1: Why machine learning for femtography?

Part 2: Inverse mapper architectures

Part 3: Web frameworks



Part 1: Why machine learning for femtography?

The current QCD global analysis paradigm

GPD

PDF

Hadron Structure

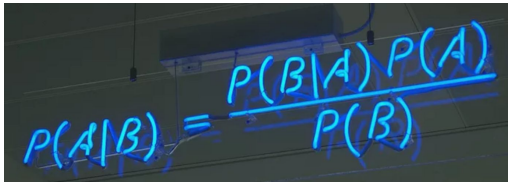
TMD PDF

FF

Hadronization

TMD FF

Factorization



Bayesian Inference

Lat.

Exp.

USQCD

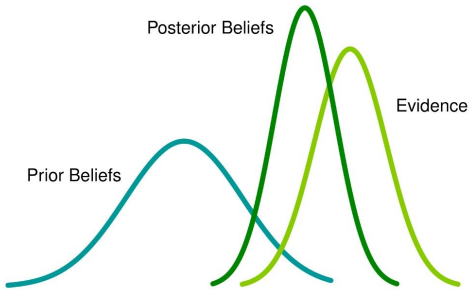
Extended Twisted Mass Collaboration

CERN

Jefferson Lab

KEK

BROOKHAVEN NATIONAL LABORATORY



The Bayesian inference

Experiments = theory + errors

$$d\sigma_{\rm DIS} = \sum_i H_i^{\rm DIS} \otimes f_i$$

$$d\sigma_{\rm DY} = \sum_{ij} H_{ij}^{\rm DY} \otimes f_i \otimes f_j$$

$$d\sigma_{\rm SIA} = \sum_i H_i^{\rm SIA} \otimes d_i$$

$$d\sigma_{\rm SIDIS} = \sum_{ij} H_{ij}^{\rm SIDIS} \otimes f_i \otimes d_j$$

Hadron Structure

Hadronization

RGE boundary conditions

$$f_i(\xi, \mu_0^2) = N_i \xi^{a_i} (1-\xi)^{b_i} (1 + \ldots)$$

$$d_i(\zeta, \mu_0^2) = N_i \zeta^{a_i} (1-\zeta)^{b_i} (1 + \ldots)$$

$$\mathbf{a} = (N_i, a_i, b_i, \ldots)$$

Posterior distribution

Prior distribution

$$\rho(\mathbf{a}|\text{data}) \sim \mathcal{L}(\mathbf{a}, \text{data})\pi(\mathbf{a})$$

Likelihood

$$\mathcal{L}(\boldsymbol{a}, \text{data}) = \exp\left[-\frac{1}{2}\chi^2(\boldsymbol{a}, \text{data})\right]$$

$$\mathrm{E}[f_i(\xi,\mu^2)] = \int \mathrm{d}^n\mathbf{a}\ \rho(\mathbf{a}|\text{data}) f_i(\xi,\mu^2;\mathbf{a})$$

$$\mathrm{V}[f_i(\xi,\mu^2)] = \int \mathrm{d}^n\mathbf{a}\ \rho(\mathbf{a}|\text{data}) \left[f_i(\xi,\mu^2;\mathbf{a}) - \mathrm{E}[f_i(\xi,\mu^2)]\right]^2$$

The inverse problem

Parametrization d.o.f.

Forward mapping

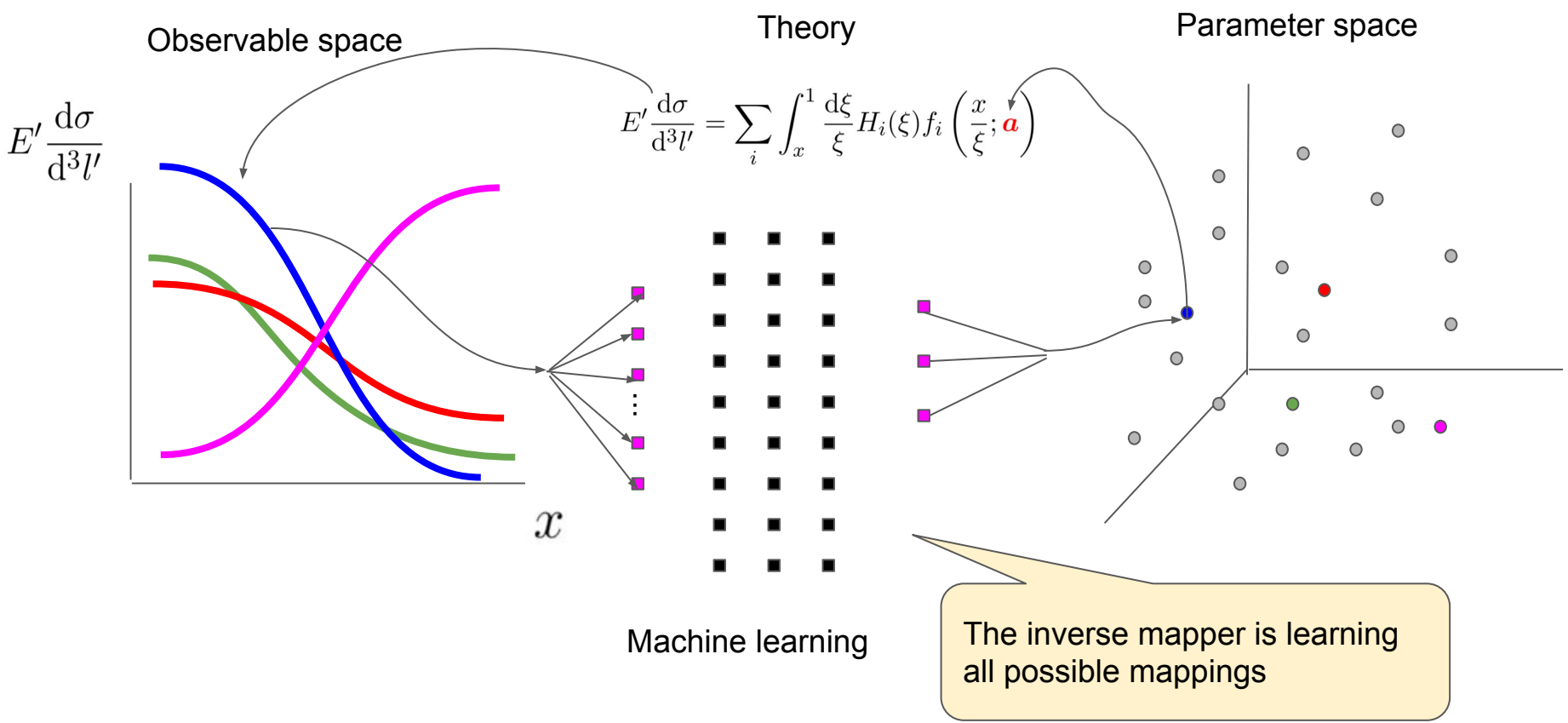
Experimental observable

$$E' \frac{\mathrm{d}\sigma^{\text{DIS}}}{\mathrm{d}^3 l'} = \sum_i \int_x^1 \frac{\mathrm{d}\xi}{\xi} H_i(\xi) f_i\left(\frac{x}{\xi}; \boldsymbol{a}\right)$$

Backward mapping

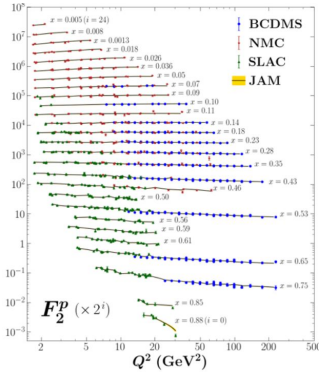
Machine learning

Training the inverse mapper

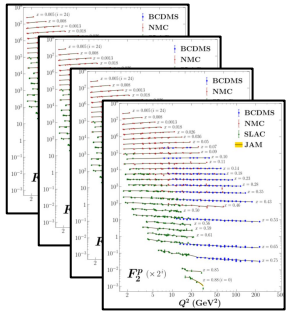


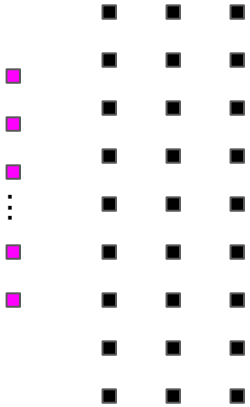
Parameter inference

Original data

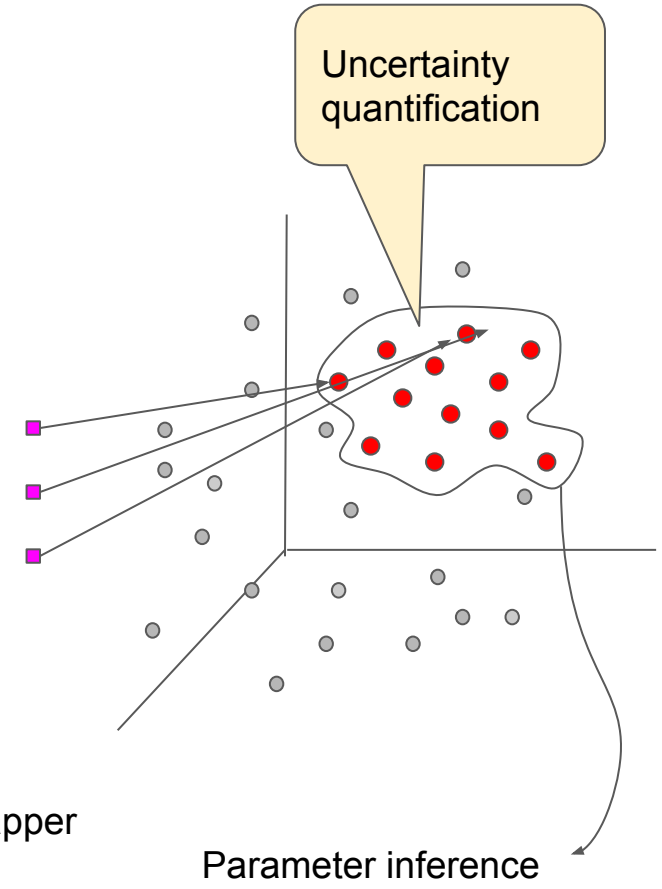


Replica data





Trained inverse mapper



Parameter inference

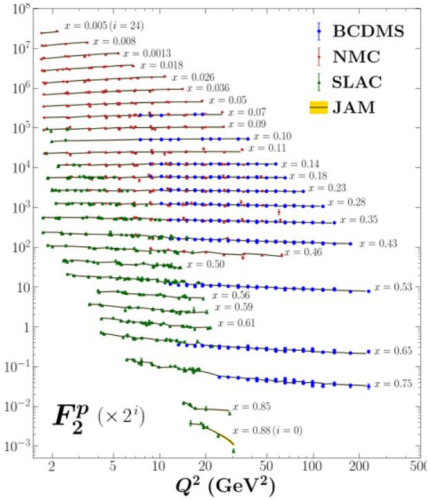
$$\rho(\mathbf{a}|\text{data}) \sim \mathcal{L}(\mathbf{a}, \text{data})\pi(\mathbf{a})$$

So why do we need **inverse mappers**?

1) Manipulate data input

Collecting MC samples is too expensive

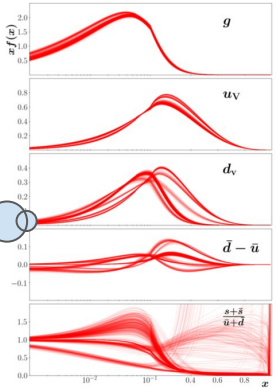
$$\rho(\mathbf{a}|\text{data}) \sim \mathcal{L}(\mathbf{a}, \text{data})\pi(\mathbf{a})$$



What happens if we remove … data ?

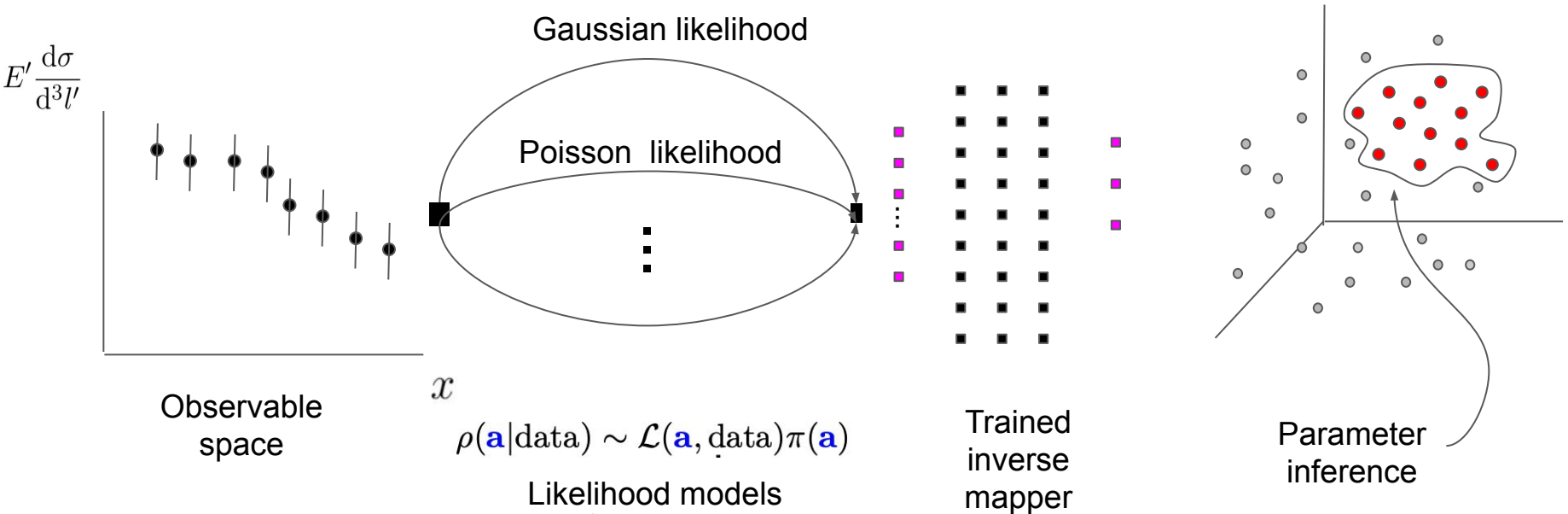
Where do we need more experiments?

"Global analysis is a kind of a sausage" … **how to unpack it**?



What data are forcing … to be …?

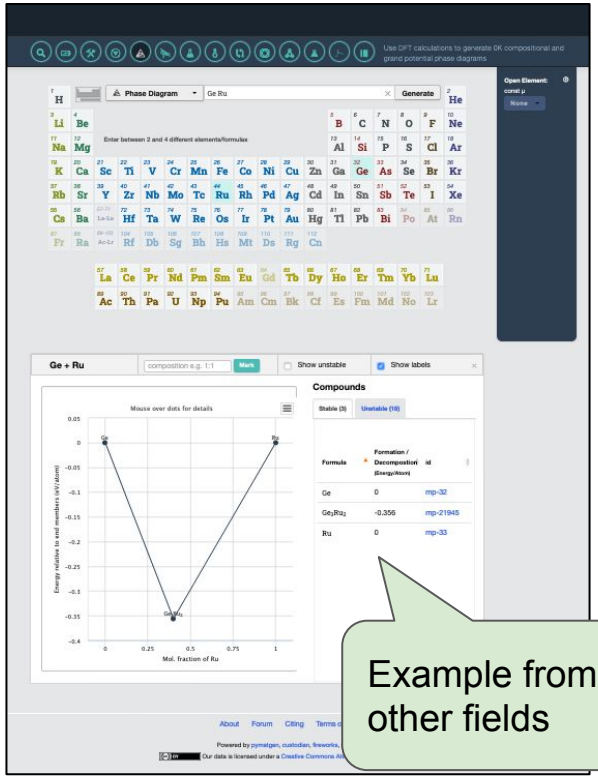
2) Bayesian inference modeling



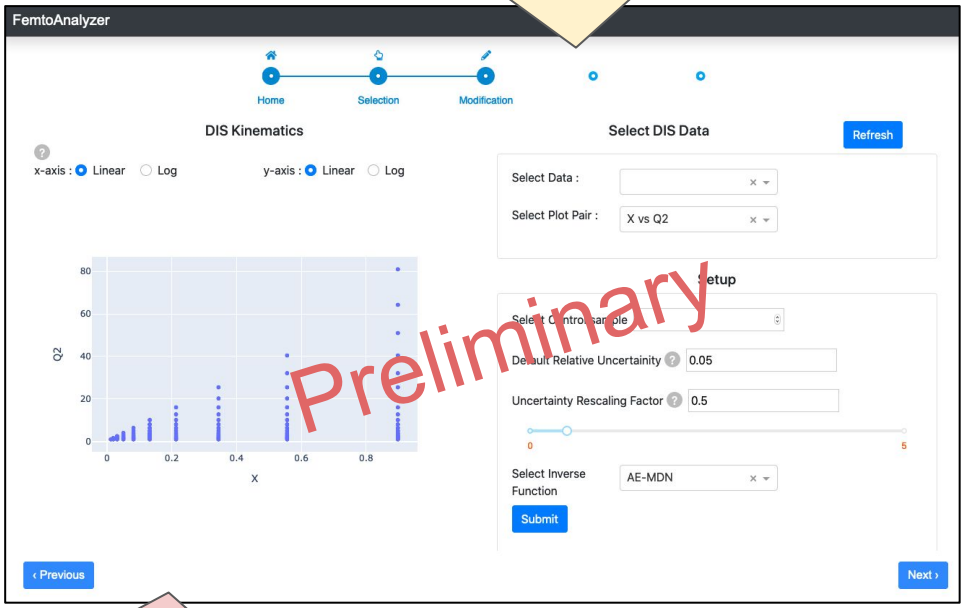
Existing methodologies are prohibitively expensive for such studies

3) Towards cloud-based global analysis framework

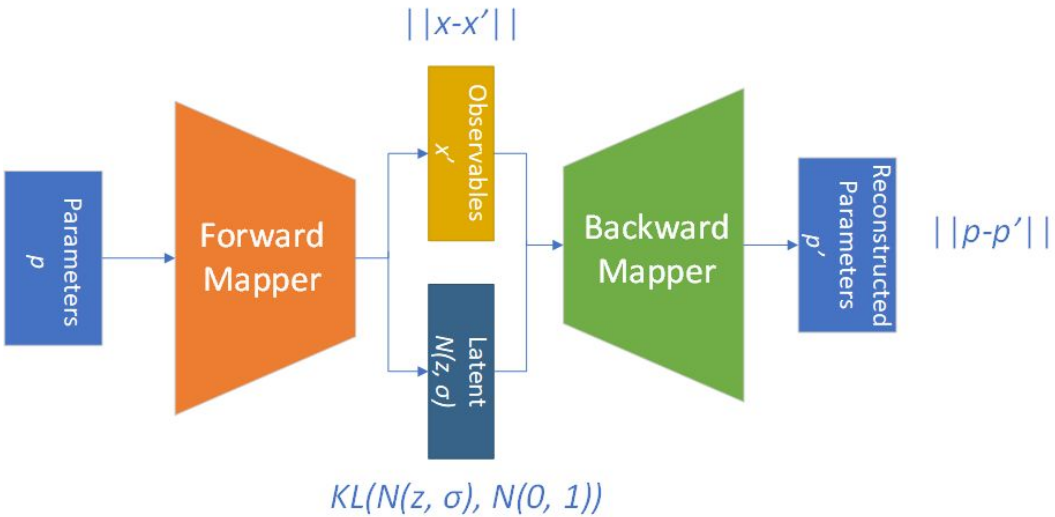
The Materials project



Accessible to a broad community

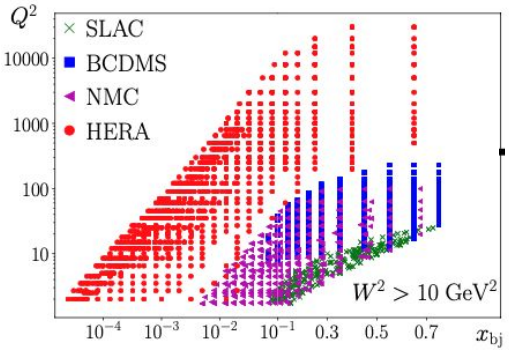


Interactive FemtoAnalyzer



Part 2: Inverse mapper architectures

Designing the inverse mappers



Grid-based inverse mapper (phase I)

Cross section 1 (x_1,Q2_1)

Cross section 2 (x_2,Q2_2)

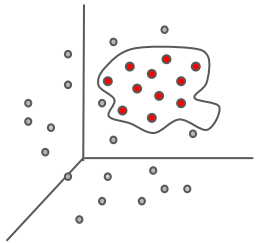
Cross section 3 (x_3,Q2_3)

x

Q2

Cross section

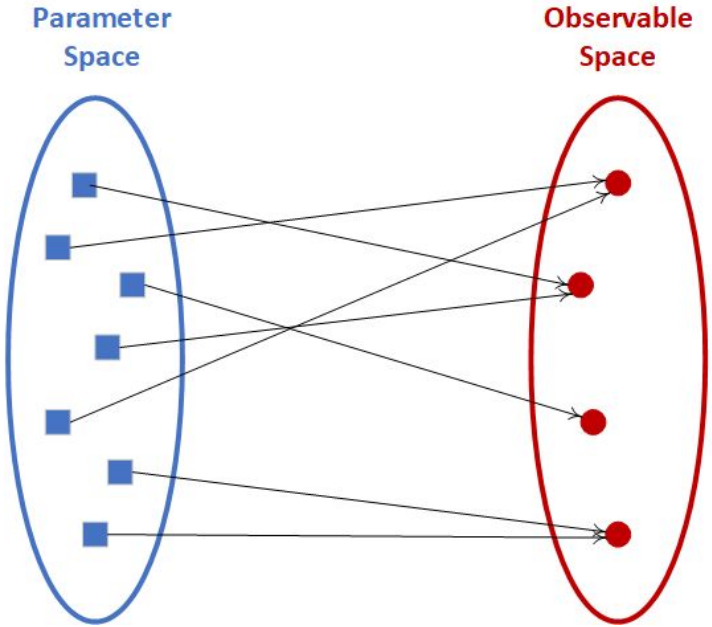
Grid-independent inverse mapper (phase II)



Parameter inference

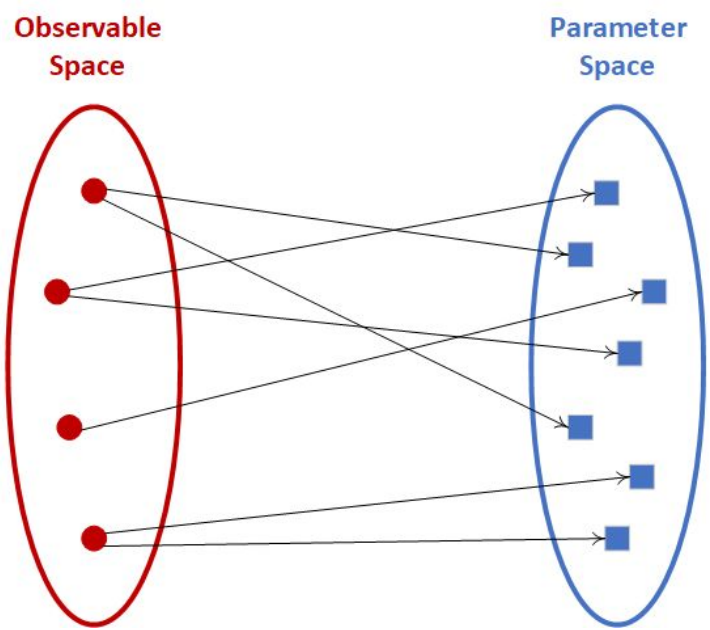
Ambiguity in inverse problems

Forward Mapper

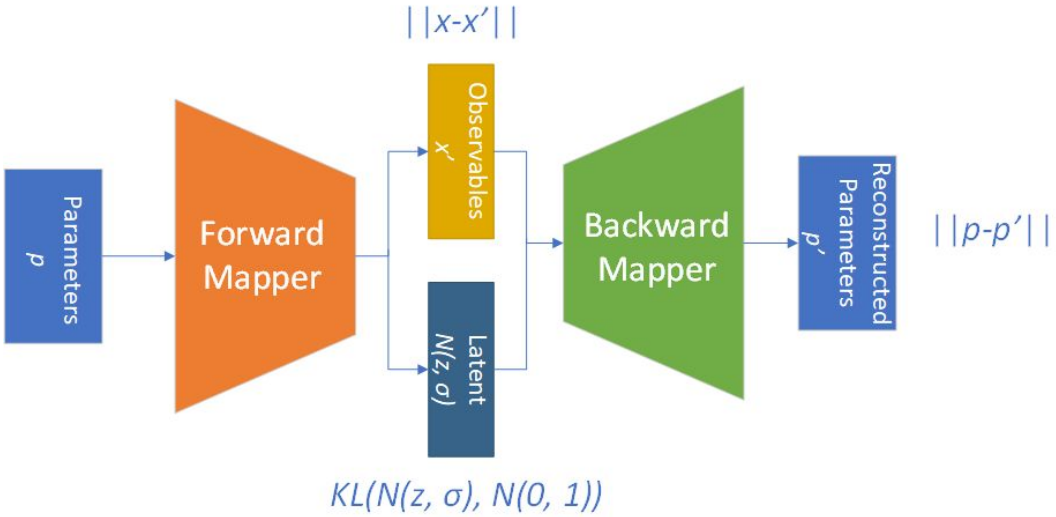


Backward Mapper

Ambiguous



Grid-independent inverse mapper: Variational Autoencoder (VAE)

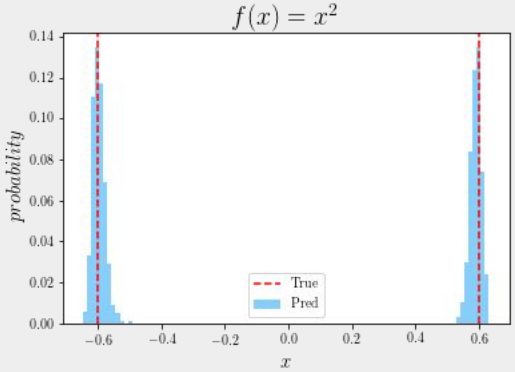


- Better than previous models
- Remove the grid dependence
- Highly accurate
- No Gaussian mixture assumption

Developed in Phase II
(5/1/2020 ~ 7/31/2020)

Toy problems with multiple solutions

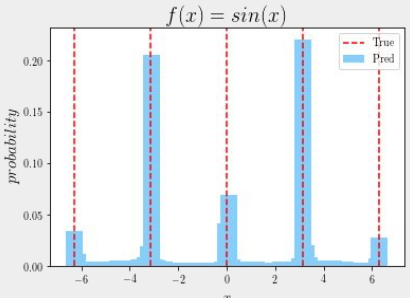
f(x) = x^2



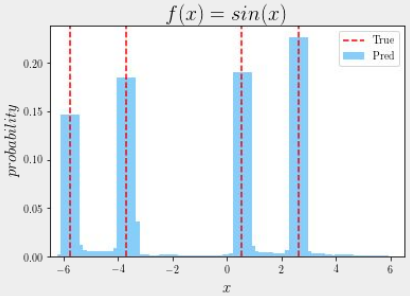
f(x) = 0.36

Two Solutions

f(x) = sin(x)



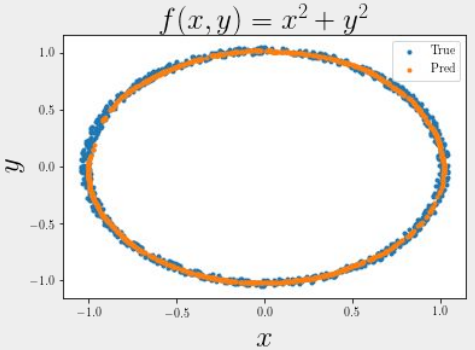
f(x) = 0



f(x) = 0.5

Multiple Finite Solutions

f(x, y) = x^2+y^2

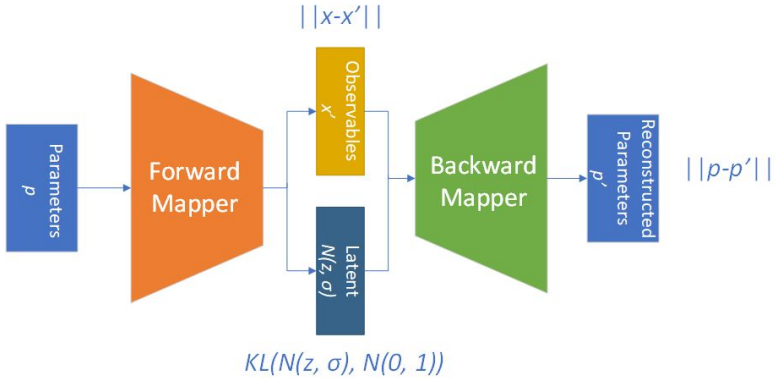


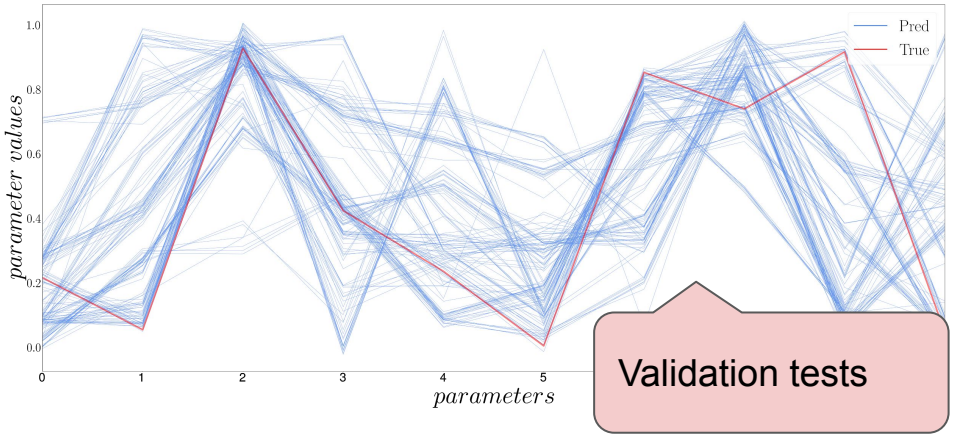
f(x, y) = 1.0

Infinite Solutions

Does it work for DIS?

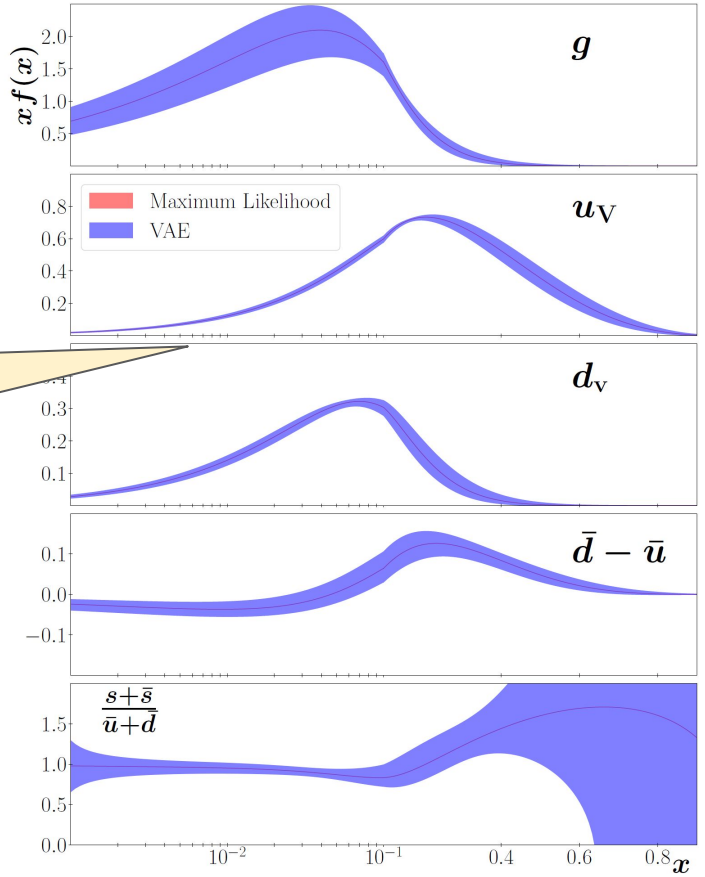
M. Almaeen *et al.* (in preparation, 2020)



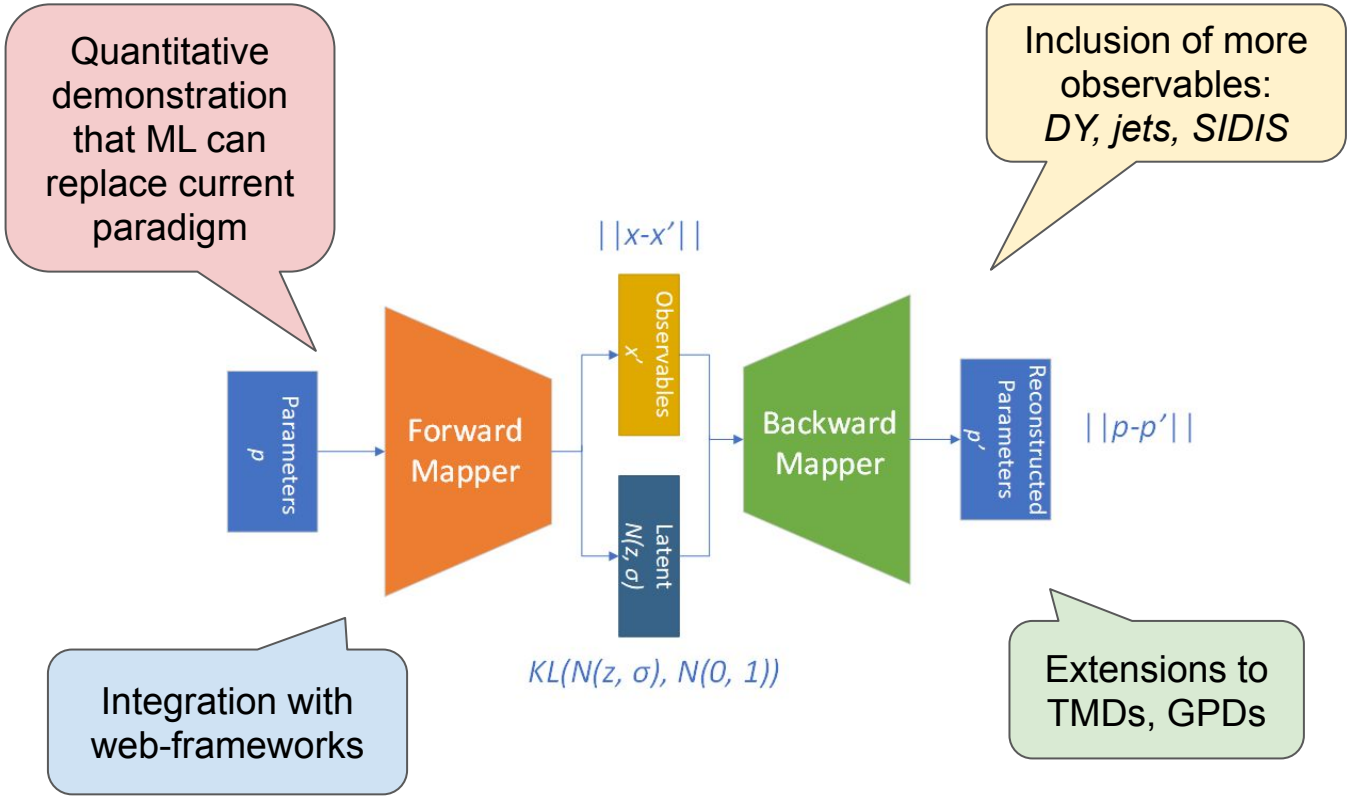


Validation tests

Inverse mapper in action!

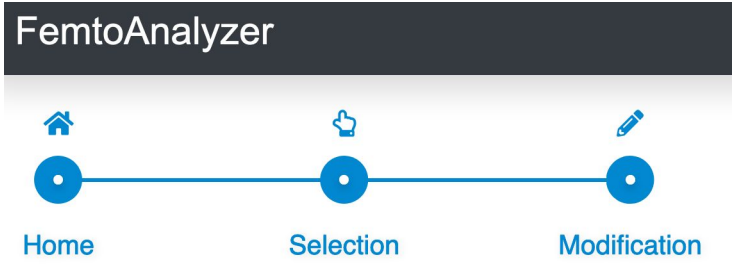


Where do we go from here?

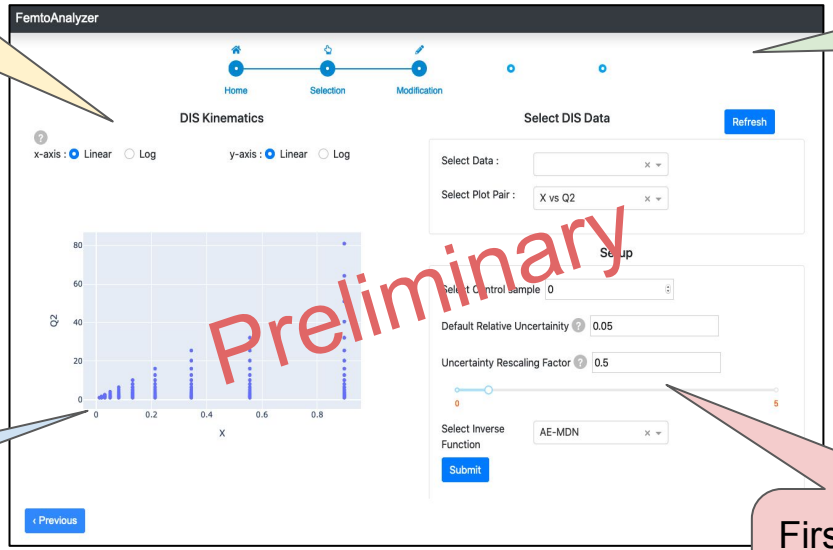


Part 3: Web frameworks

Status of web framework



Currently using toy DIS-like with grid-based models



Deployed on *Heroku* web service

First prototypes for data manipulation tools

First prototypes for 1D hadron structure visualization

Where do we go from here?

Where can we host the web application $$$?

Build an AI-based database

A tool for JLab and EIC community

FemtoAnalyzer as an AI agent

The workforce of FemtoAnalyzer

Jefferson Lab

co-PI

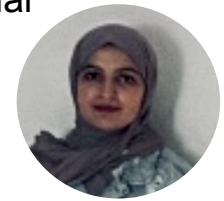
ODU

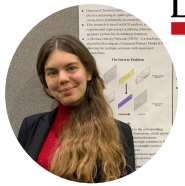
PI

DAVIDSON

Raghu DAVIDSON

ODU Manal





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ODU Heramb

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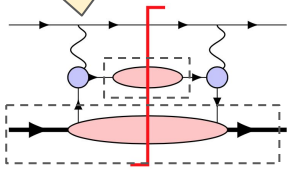
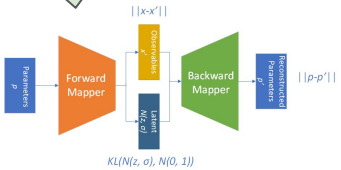
QCD Theory



Rida DAVIDSON

Inverse mappers



Web-interface