Next generation of QCD global analysis for femtography

Nobuo Sato

CNF - Experiment and theory interactions

Feb 2021

Disclaimer

Context of discussion: QCD global analysis of PDFs, fragmentation functions and TMDs

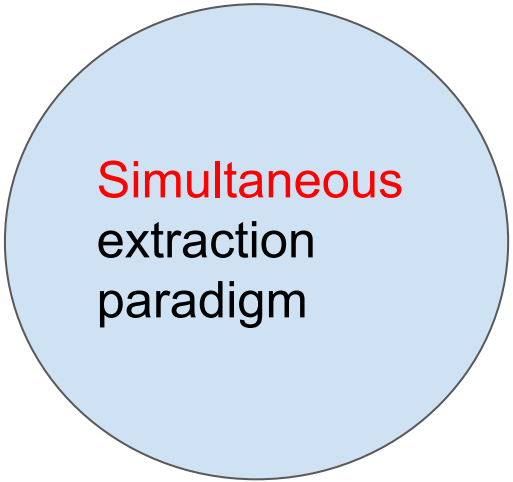
The ideas can be extended to GPDs

Main points

Simultaneous extraction paradigm

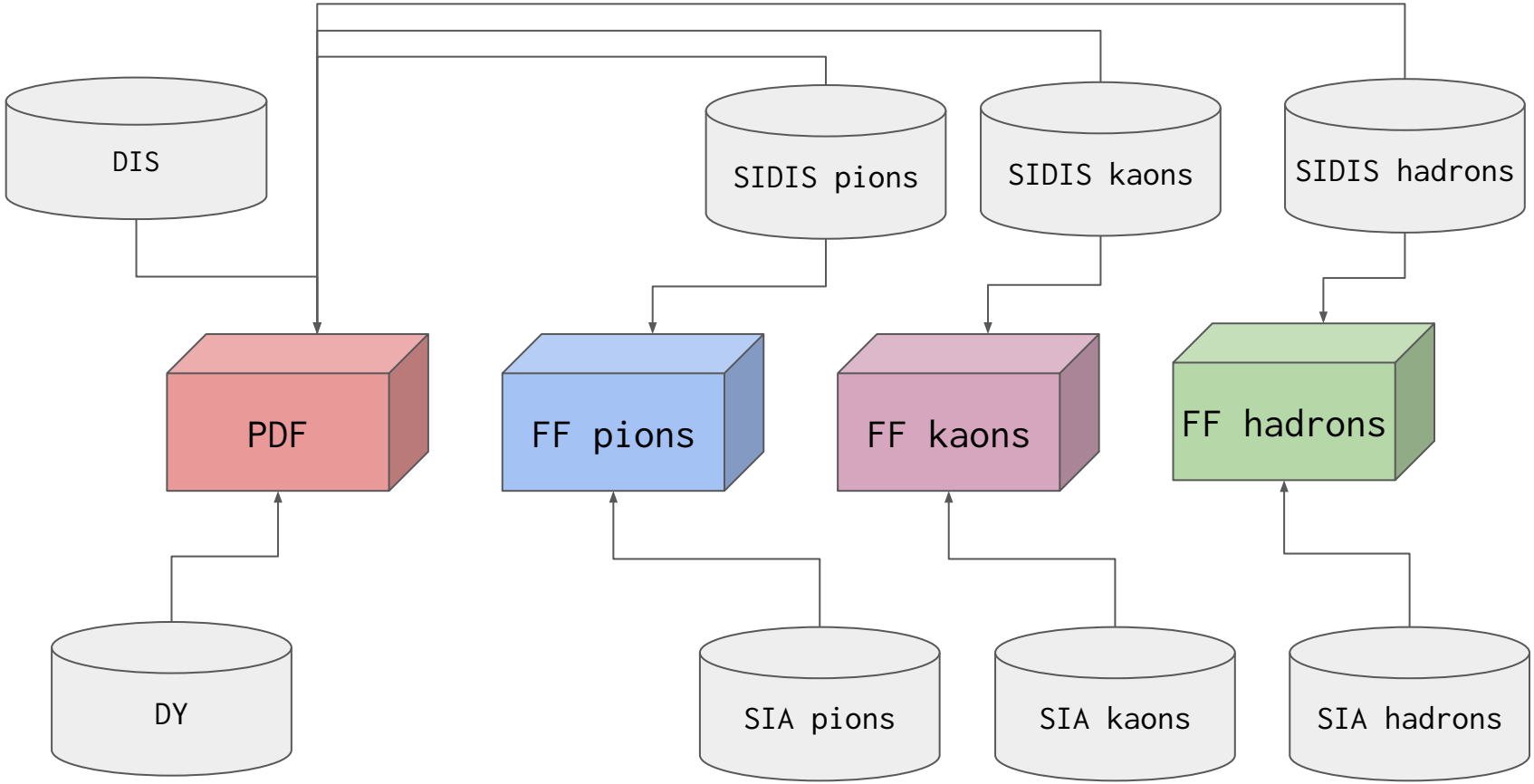
Reliable extraction procedure: MC methods

Use of modern Machine Learning

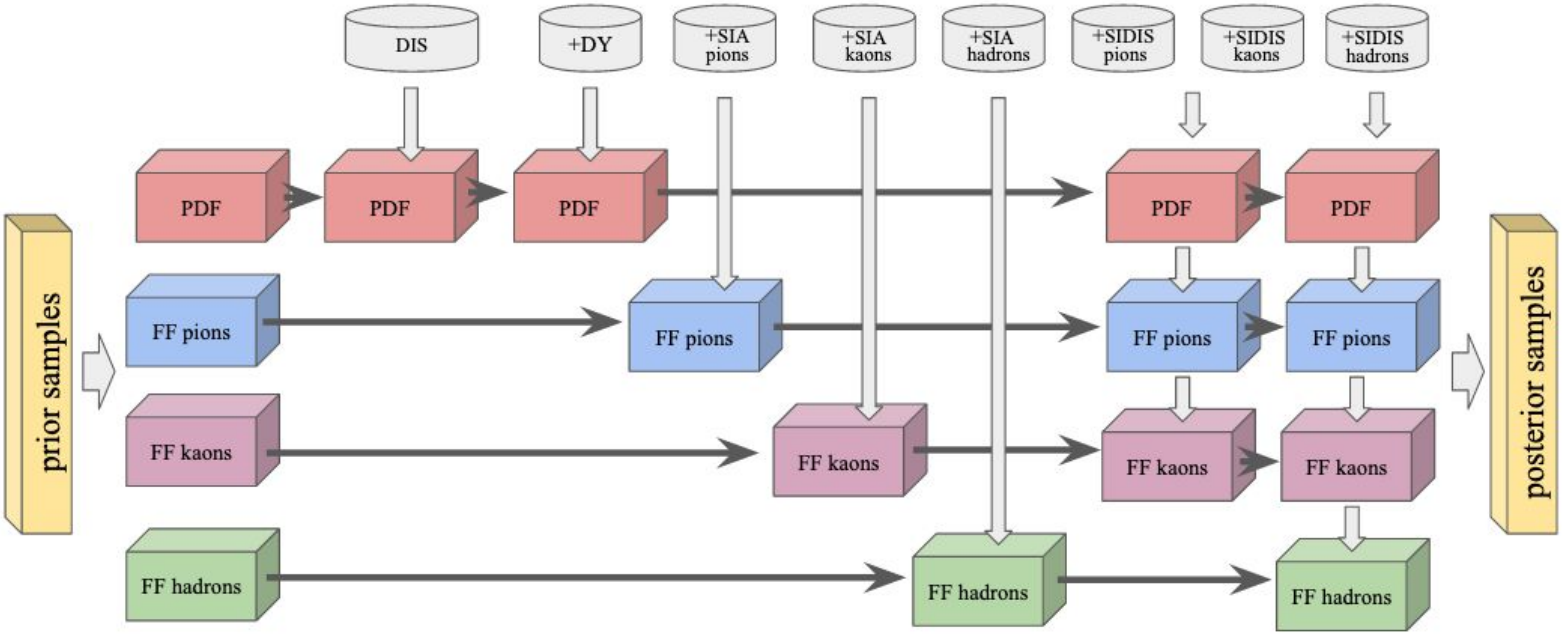


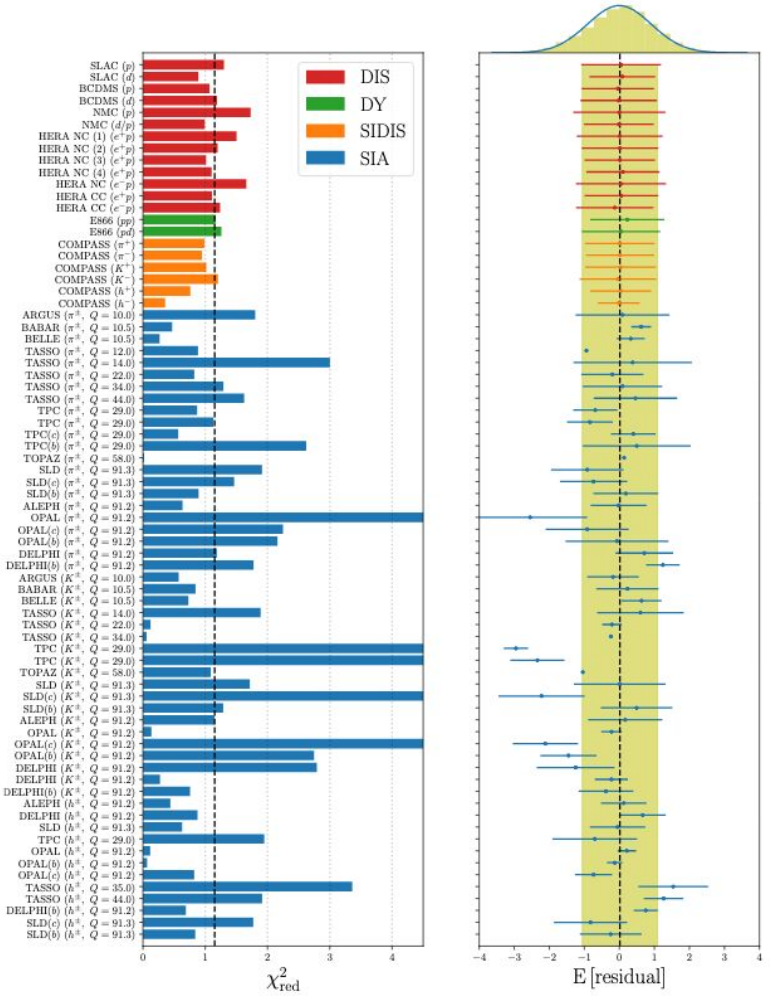
Example: JAM20-SIDIS

Moffat, Melnitchouk, Rogers, NS

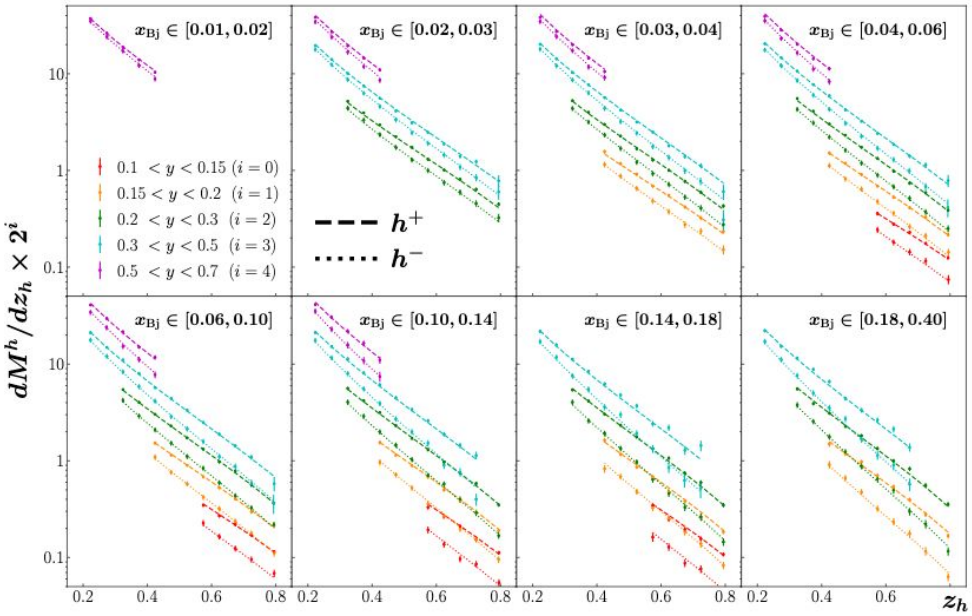

DIS
SIDIS pions
SIDIS kaons
SIDIS hadrons
PDF
FF pions
FF kaons
FF hadrons
DY
SIA pions
SIA kaons
SIA hadrons

Multi-step strategy

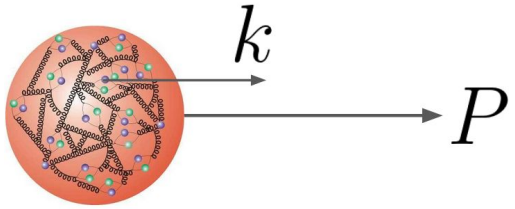


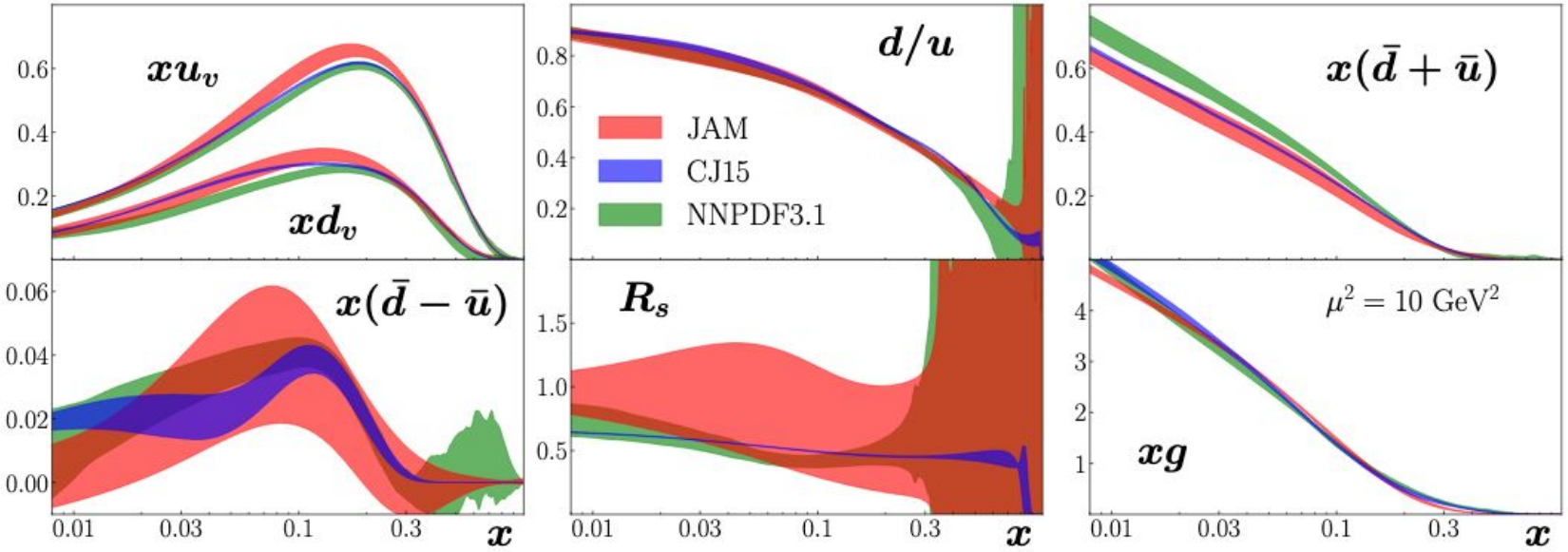


SIDIS data and theory

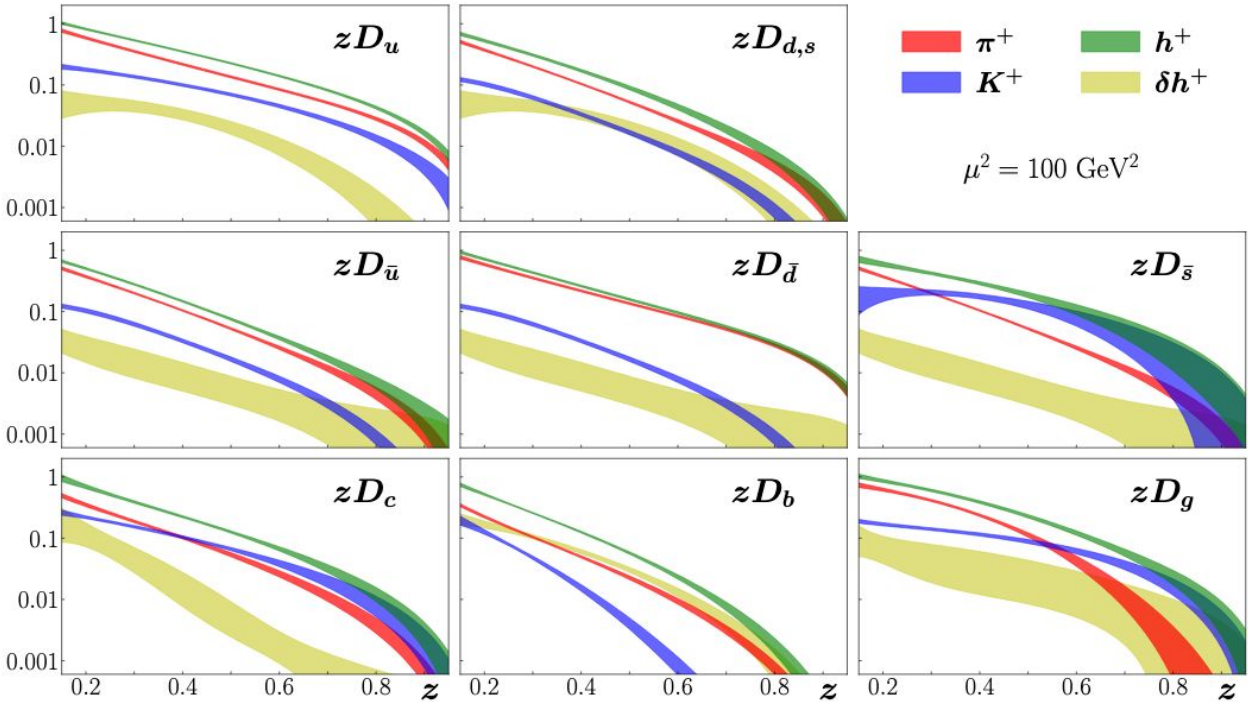


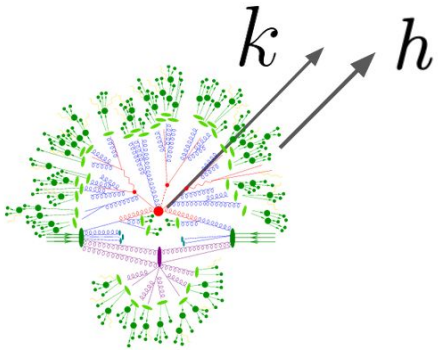
PDFs


k
P

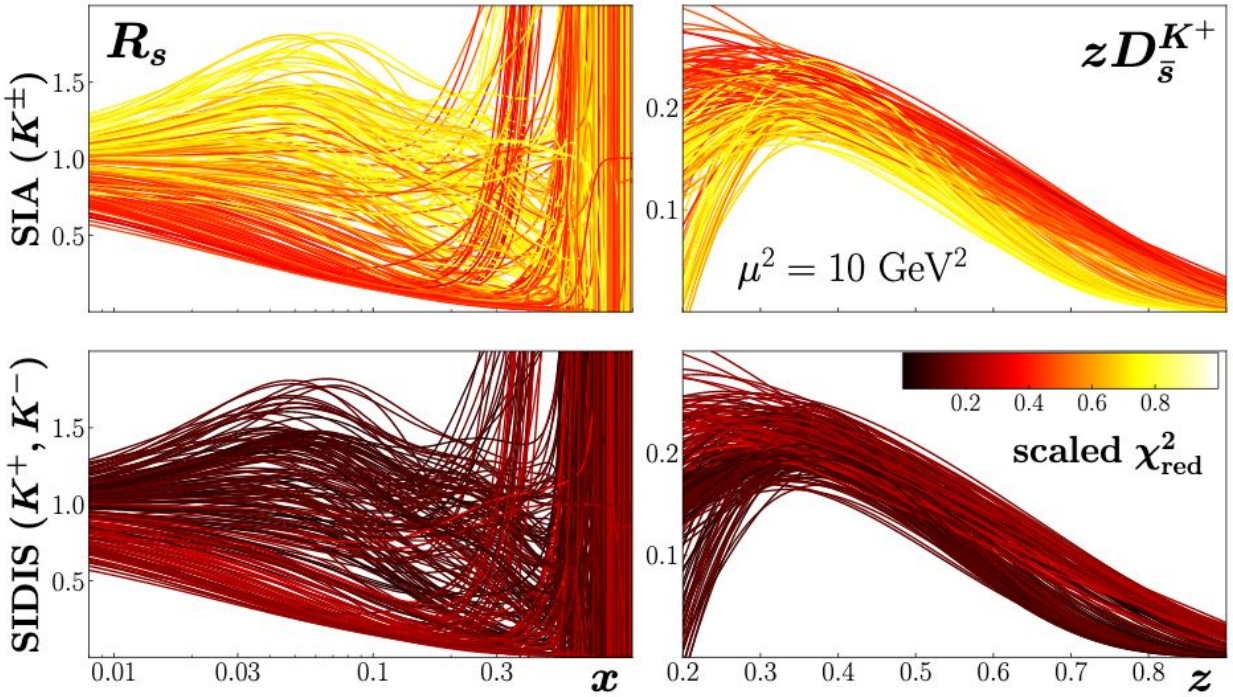

xu_v
xd_v
$x(\bar{d}-\bar{u})$
d/u
JAM
CJ15
NNPDF3.1
R_s
$x(\bar{d}+\bar{u})$
$\mu^2 = 10$ GeV^2
xg
x

Fragmentation Functions



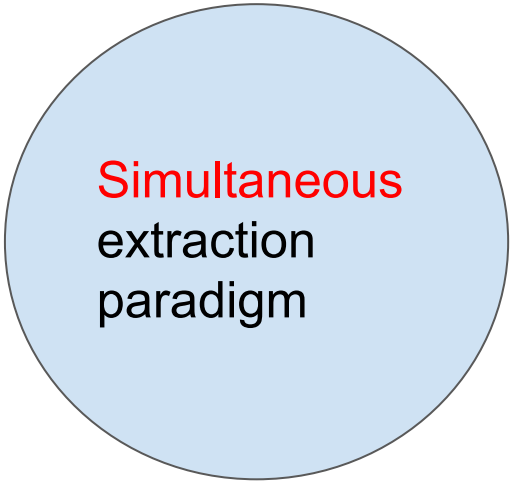


The need of simultaneous extraction paradigm



$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

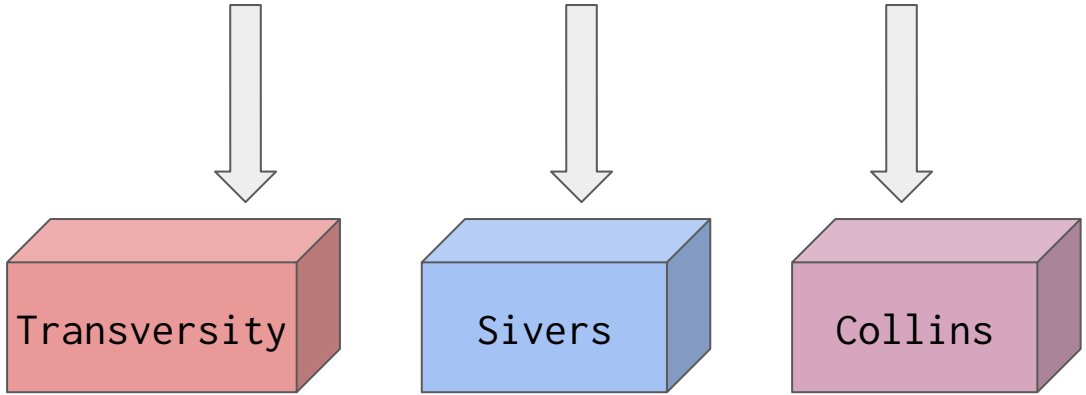
The simultaneous fit of PDFs and FFs provides new insights on nucleon strangeness

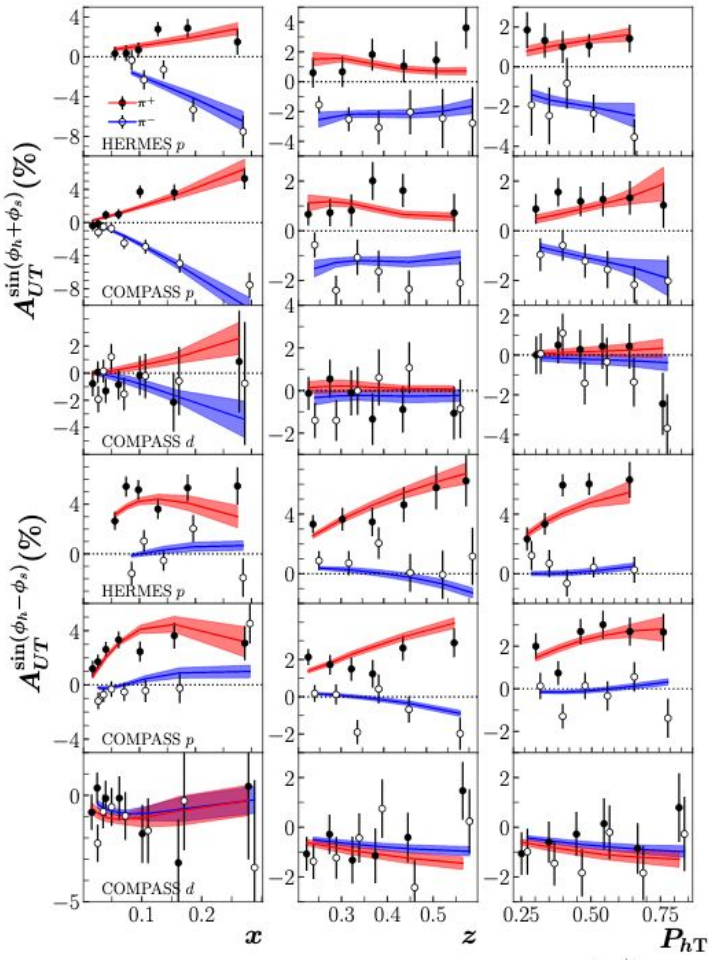


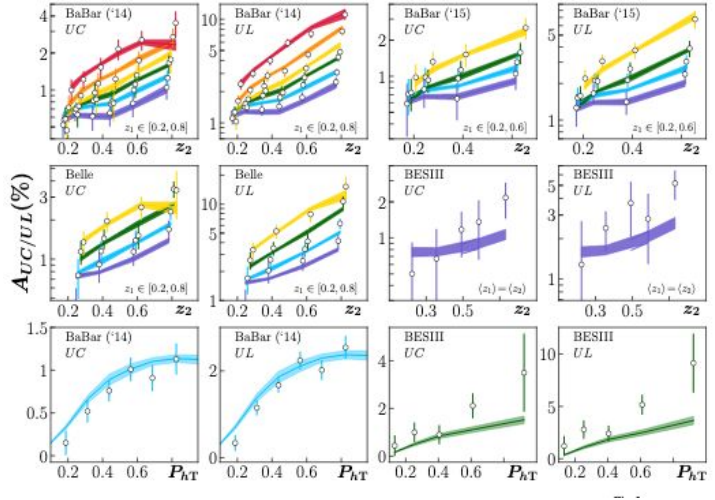
Example: JAM20-TMD+CT3

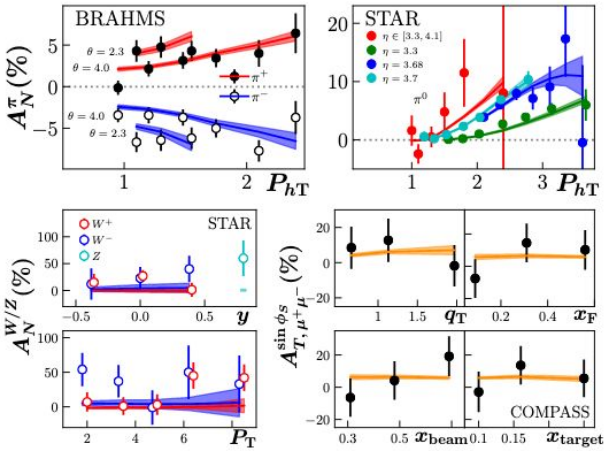
Cammarota, Gamberg, Kang, Miller, Pitonyak, Prokudin, Rogers, NS

Observable	Reactions
$A_{\mathrm{SIDIS}}^{\mathrm{Siv}}$	$e + (p,d)^{\uparrow} \to e + (\pi^+, \pi^-, \pi^0) + X$
$A_{\mathrm{SIDIS}}^{\mathrm{Col}}$	$e + (p,d)^{\uparrow} \to e + (\pi^+, \pi^-, \pi^0) + X$
$A_{\mathrm{SIA}}^{\mathrm{Col}}$	$e^+ + e^- \to \pi^+\pi^-(UC, UL) + X$
$A_{\mathrm{DY}}^{\mathrm{Siv}}$	$\pi^- + p^{\uparrow} \to \mu^+\mu^- + X$
$A_{\mathrm{DY}}^{\mathrm{Siv}}$	$p^{\uparrow} + p \to (W^+, W^-, Z) + X$
A_N^h	$p^{\uparrow} + p \to (\pi^+, \pi^-, \pi^0) + X$

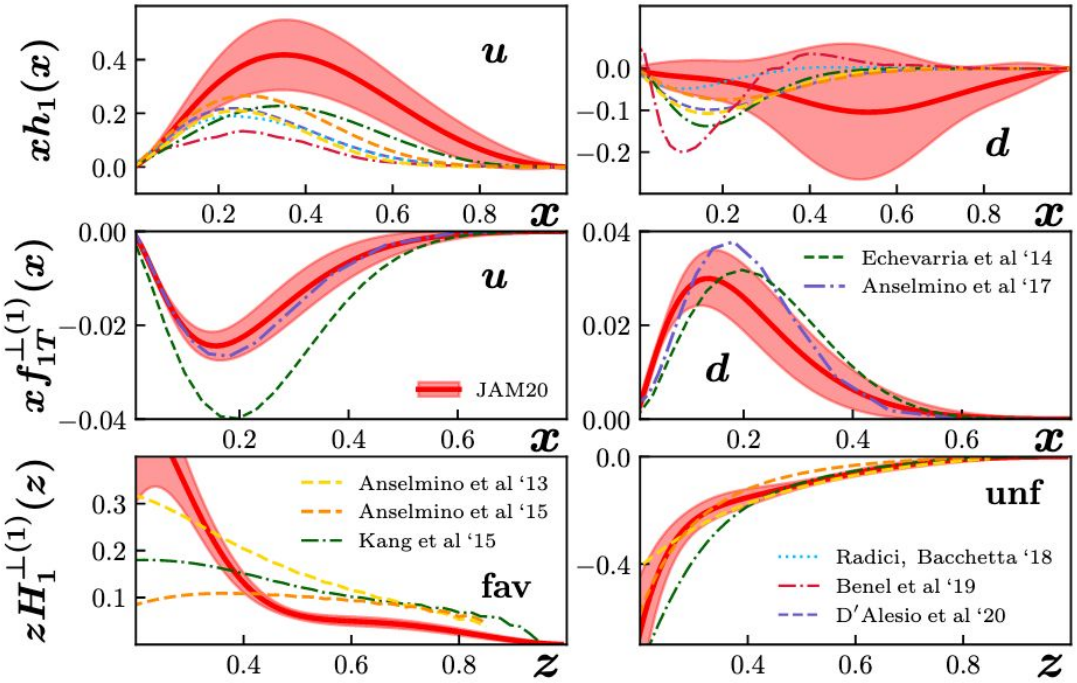


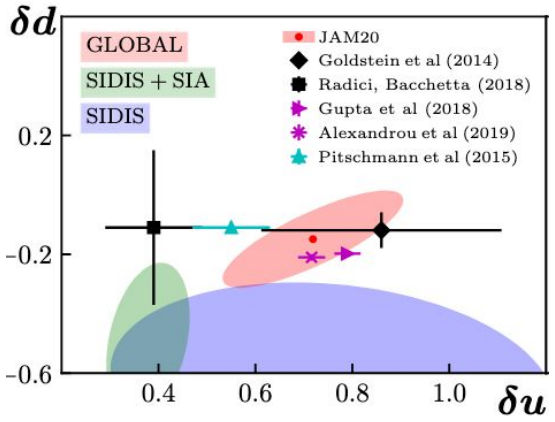

HERMES p
COMPASS p
COMPASS d
HERMES p
COMPASS p
COMPASS d
$A_{UT}^{\sin(\phi_h+\phi_s)}$ (%)
$A_{UT}^{\sin(\phi_h-\phi_s)}$ (%)
π^+
π^-
x
z
P_{hT}

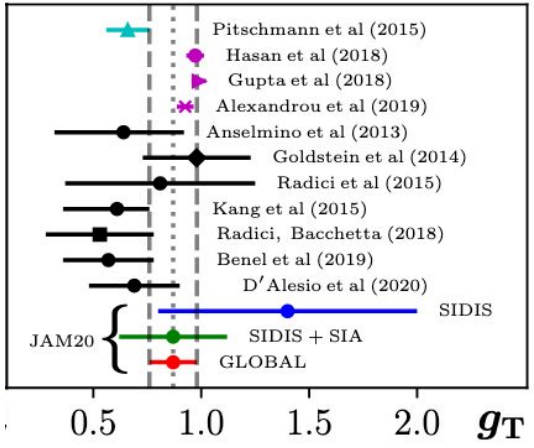

BaBar ('14) UC
BaBar ('14) UL
BaBar ('15) UC
BaBar ('15) UL
Belle UC
Belle UL
BESIII UC
BESIII UL
$A_{UC/UL}$ (%)
z_2
P_{hT}


BRAHMS
STAR
A_N^{π} (%)
π^+
π^-
π^0
P_{hT}
$A_N^{W/Z}$ (%)
W^+
W^-
Z
y
P_T
$A_{T,\mu^+\mu^-}^{\sin\phi_S}$ (%)
q_T
x_F
COMPASS
x_{beam}
x_{target}

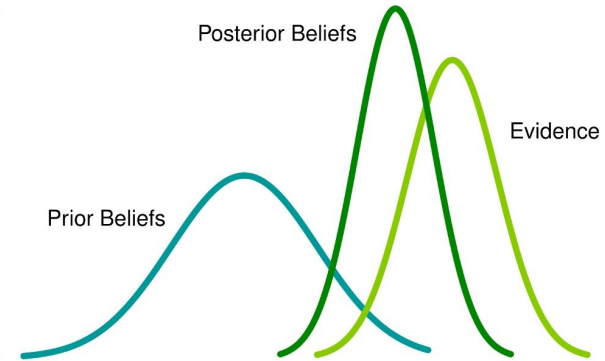
The need of simultaneous extraction paradigm







Reliable extraction procedure:
MC methods



Bayesian inference

T. Bayes.

The Bayes theorem

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

This is a choice

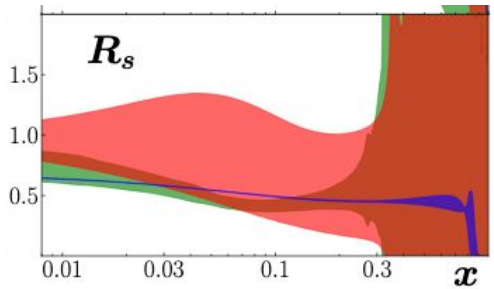
Min, Max, penalties, regulators etc

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

This is impractical

$$\mathrm{E}[\mathcal{O}] = \int d^n a\ \rho(\boldsymbol{a}|\text{data})\ \mathcal{O}(\boldsymbol{a})$$

$$\mathrm{V}[\mathcal{O}] = \int d^n a\ \rho(\boldsymbol{a}|\text{data})\ \left[\mathcal{O}(\boldsymbol{a}) - \mathrm{E}[\mathcal{O}]\right]^2$$



How do we deal with the curse of dimensionality ?

$$\mathrm{E}[\mathcal{O}] = \int d^n a \; \rho(\boldsymbol{a}|\mathrm{data}) \; \mathcal{O}(\boldsymbol{a})$$

$$\mathrm{V}[\mathcal{O}] = \int d^n a \; \rho(\boldsymbol{a}|\mathrm{data}) \; \left[\mathcal{O}(\boldsymbol{a}) - \mathrm{E}[\mathcal{O}]\right]^2$$

Option 1: Maximum likelihood

Asummes symmetric likelihood, unique solution

$$\mathrm{E}[\mathcal{O}] \simeq \mathcal{O}(\boldsymbol{a}_0)$$

Assumes Gaussian behavior around ML

$$\mathrm{V}[\mathcal{O}] = \mathrm{Hessian}, \; \mathrm{Lagrange\ multipliers}$$

How do we deal with the curse of dimensionality ?

$$\mathrm{E}[\mathcal{O}] = \int d^n a \; \rho(\boldsymbol{a}|\mathrm{data}) \; \mathcal{O}(\boldsymbol{a})$$

$$\mathrm{V}[\mathcal{O}] = \int d^n a \; \rho(\boldsymbol{a}|\mathrm{data}) \; \left[\mathcal{O}(\boldsymbol{a}) - \mathrm{E}[\mathcal{O}]\right]^2$$

Option 2: MC approach

Build an MC ensemble ($$$)

$$\mathrm{E}[\mathcal{O}] \simeq \frac{1}{N} \sum_k \mathcal{O}(\boldsymbol{a}_k)$$

$$\mathrm{V}[\mathcal{O}] = \simeq \frac{1}{N} \sum_k \left[\mathcal{O}(\boldsymbol{a}_k) - \mathrm{E}[\mathcal{O}]\right]^2$$

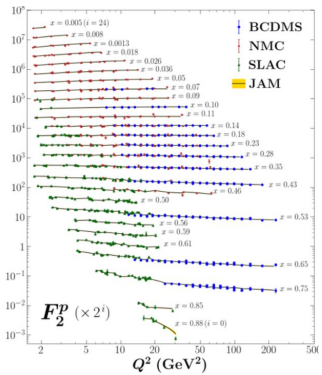
Many algorithms

- MCMC
- HMC
- Data resampling
- ...

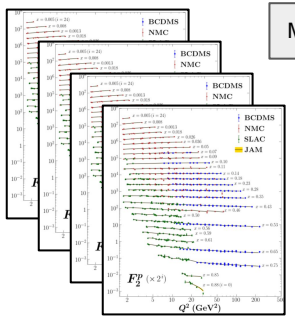
Data resampling

$$d_{k,i}^{(\text{pseudo})} = d_i^{(\text{original})} + \alpha_i \; R_{k,i}$$

Original data



Replica data

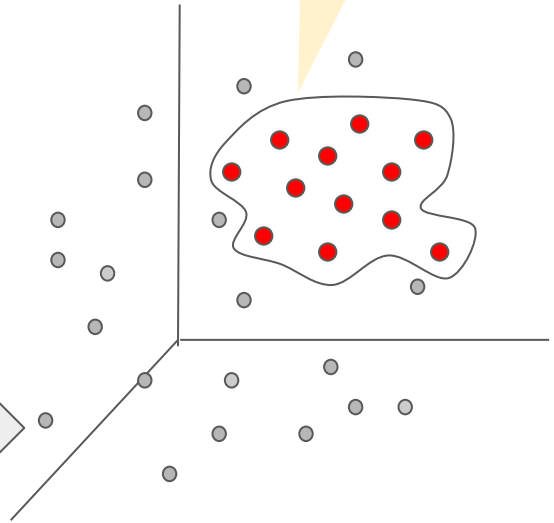


Maximum likelihood

Maximum likelihood

Maximum likelihood

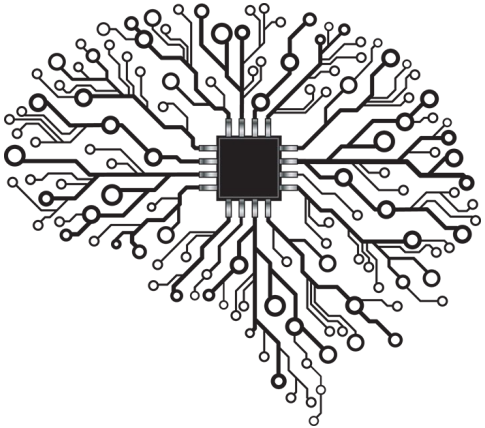
Maximum likelihood

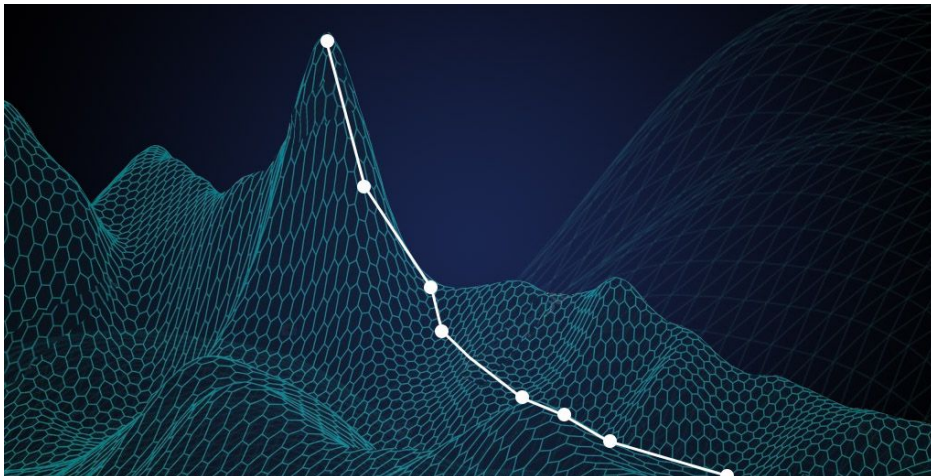


Confidence region

Parameter space

Use of modern Machine Learning

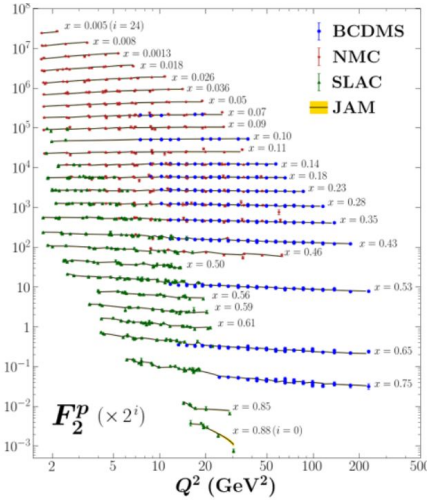




Limitation of current methodology

Collecting MC samples is too expensive

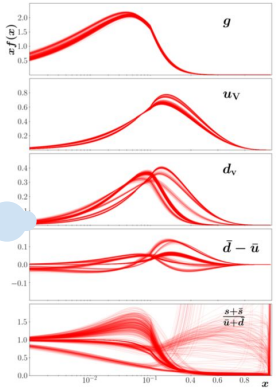
$$\rho(\mathbf{a}|\text{data}) \sim \mathcal{L}(\mathbf{a}, \text{data})\pi(\mathbf{a})$$



What happens if we remove … data ?

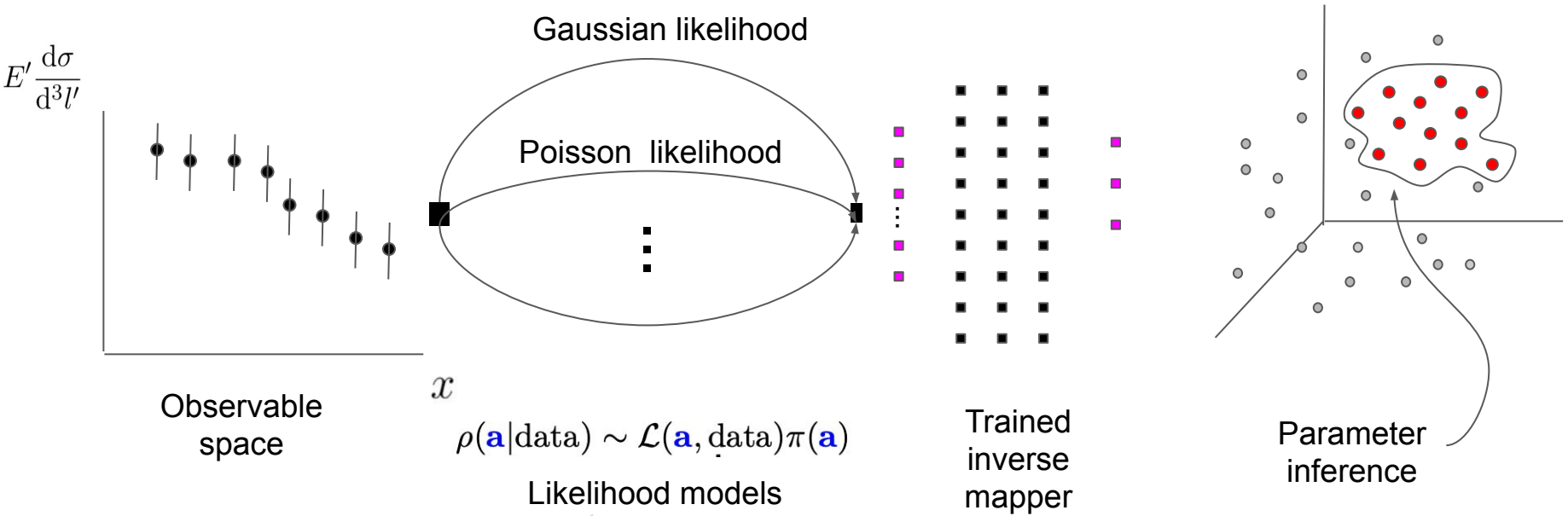
Where do we need more experiments?

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



What data are forcing … to be …?

Need to go beyond gaussian likelihoods



Existing methodologies are prohibitively expensive for such studies

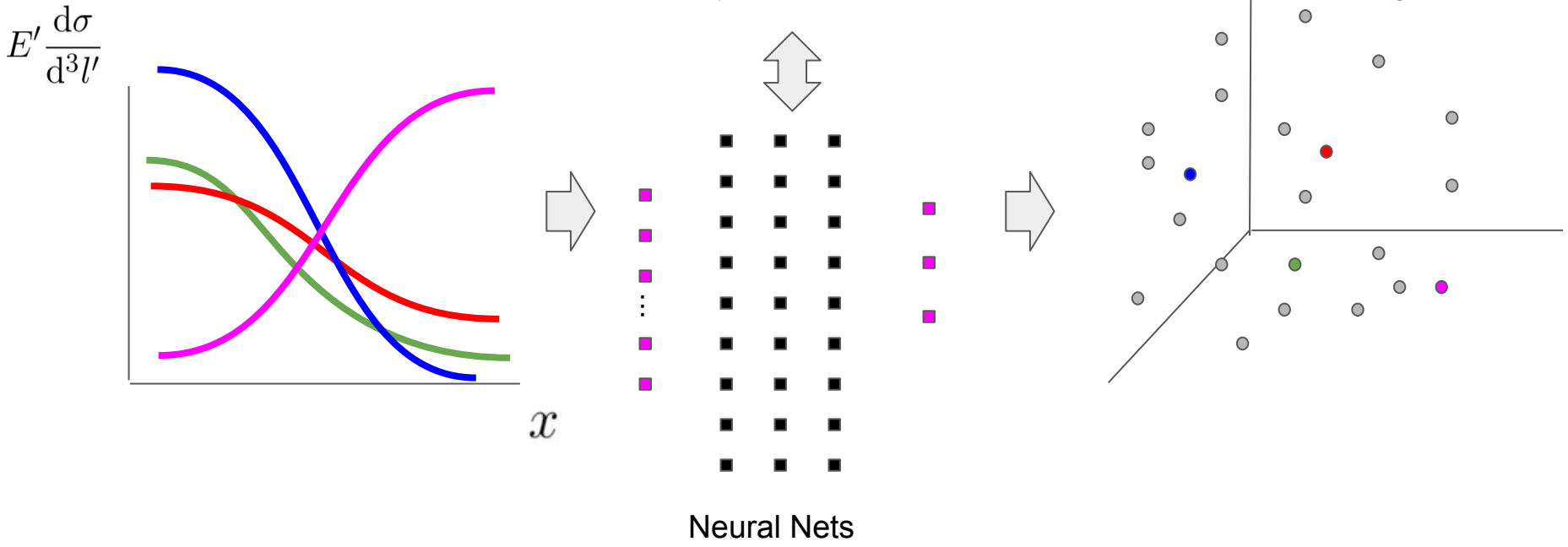
Key idea: parametrize the inverse function

Observable space

Theory

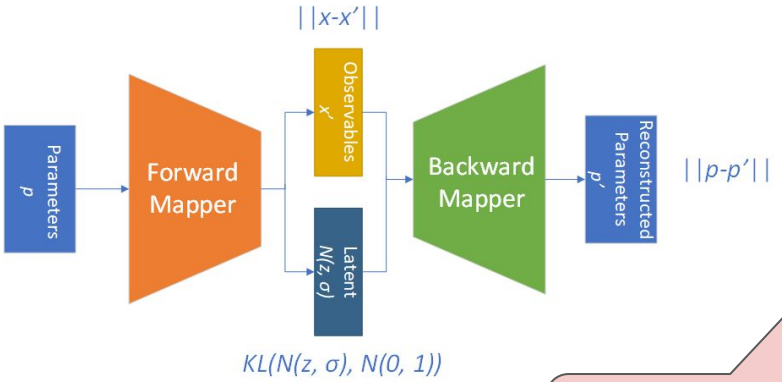
Parameter space

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



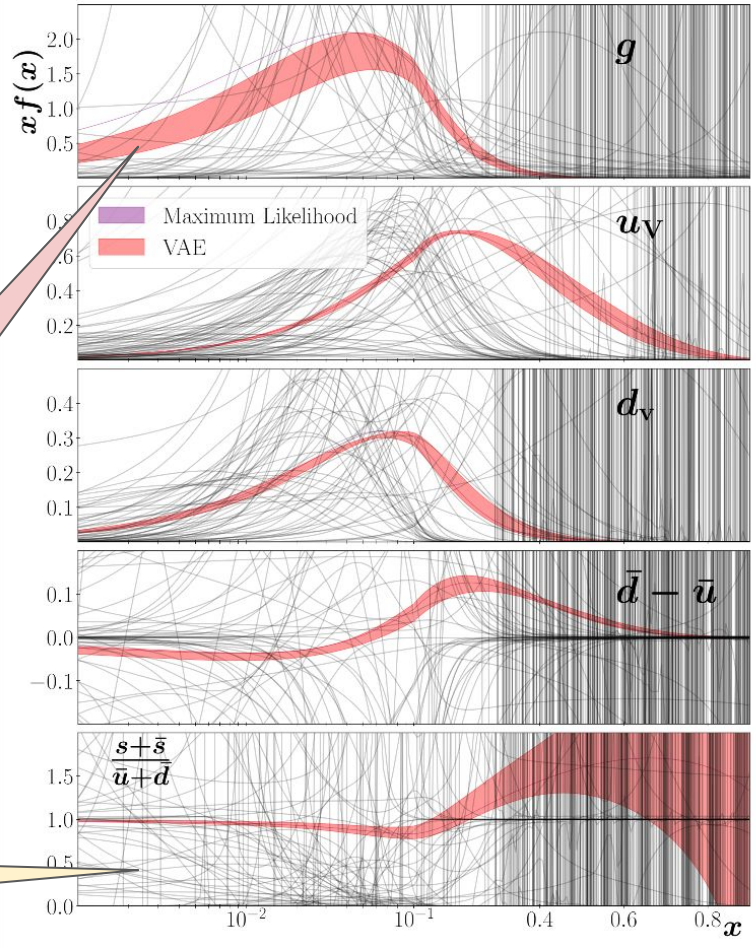
Neural Nets

Inverse mappers



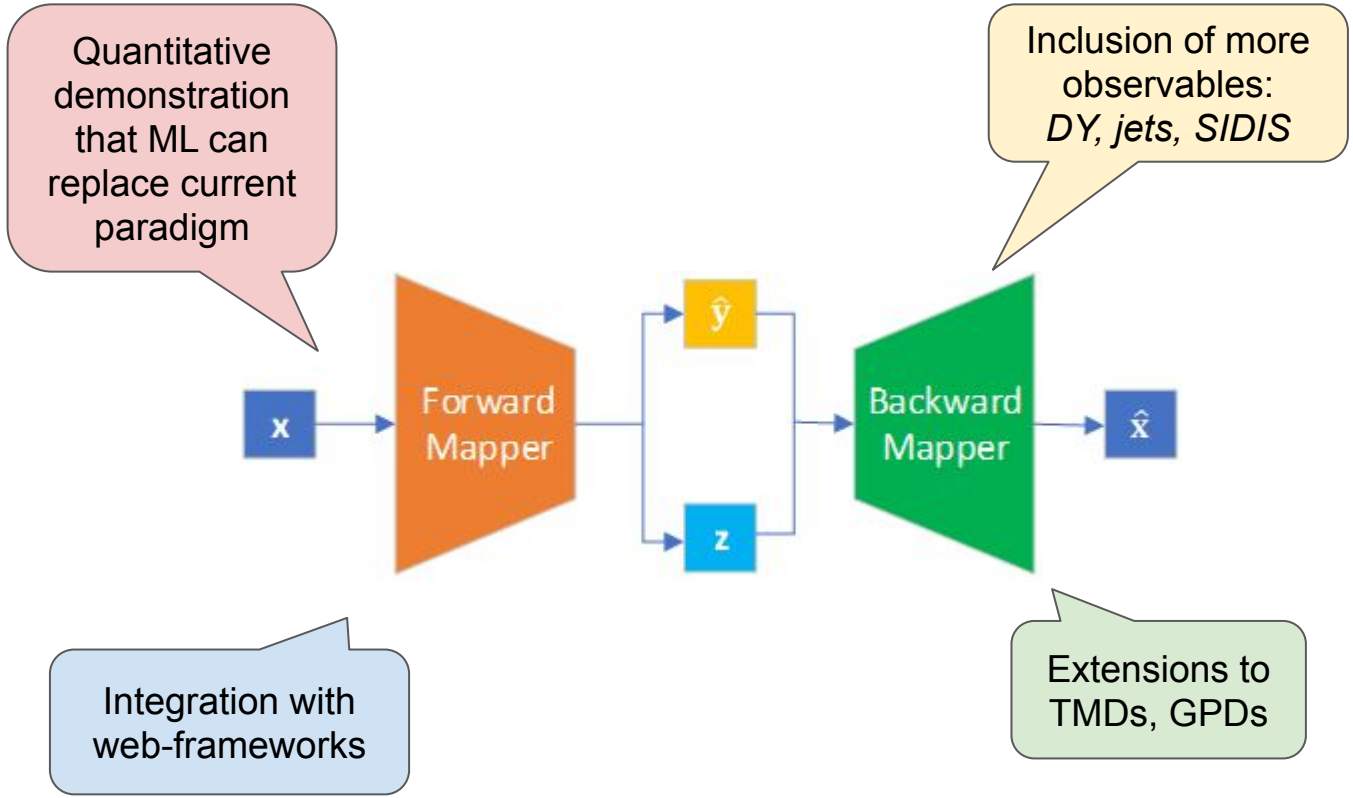
Inverse mapper Inference

Training samples

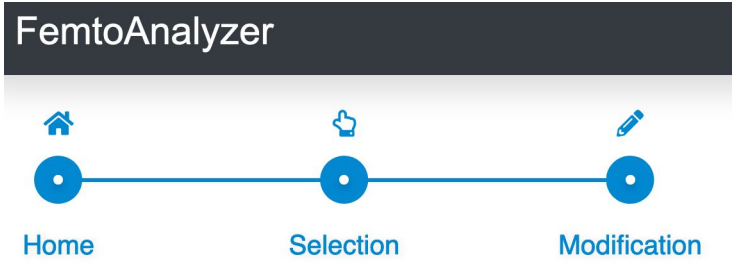


Summary and Outlook

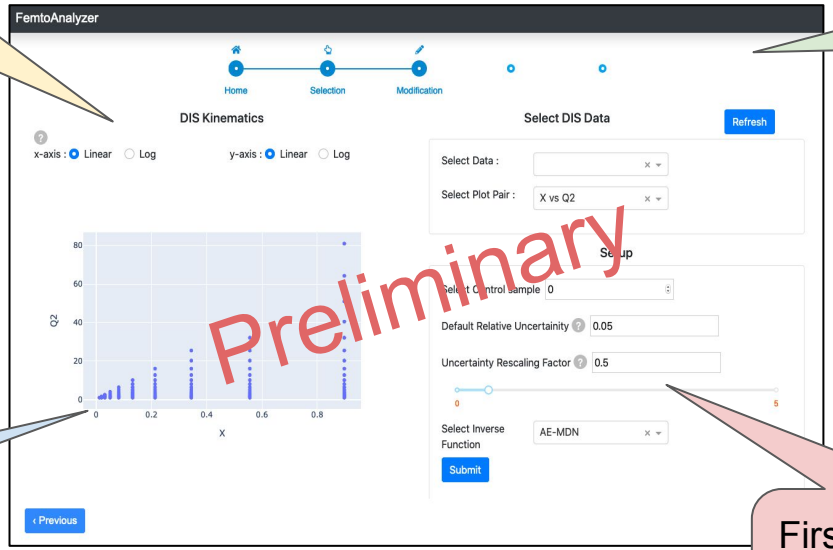
Where do we go from here?



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

The ML workforce

Jefferson Lab

co-PI

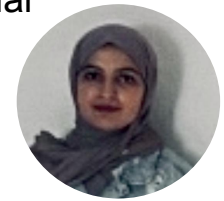
ODU

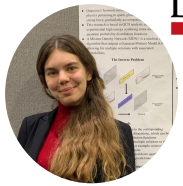
PI

DAVIDSON

Raghu DAVIDSON

ODU Manal



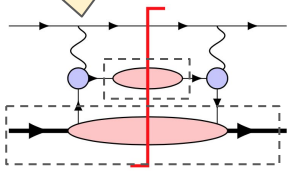


Eleni DAVIDSON

ODU Heramb

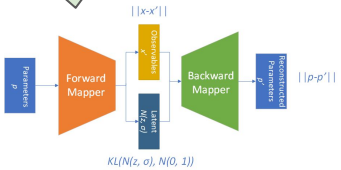
Annabel DAVIDSON

QCD Theory



Rida DAVIDSON

Inverse mappers



Web-interface