Next generation of QCD global analysis tools

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Current paradigm

- Global analysis uses Bayesian regression

- It is done via posterior sampling

\[ \rho(\alpha|\text{data}) = \mathcal{L}(\alpha, \text{data})\pi(\alpha) \]

- \(\alpha\) are the “shape” parameters for QCF
Why do we use posterior sampling?
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We know how to go from \( \alpha \) to cross sections e.g.

\[
\frac{d\sigma}{dx dQ^2} = \sum_q \int_x^1 \frac{d\xi}{\xi} H(\xi) f_q \left( \frac{x}{\xi}, \mu; \alpha \right)
\]
Why do we use posterior sampling?

- We know how to go from $\alpha$ to cross sections e.g.
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  \frac{d\sigma}{dxdQ^2} = \sum_q \int_x^1 \frac{d\xi}{\xi} H(\xi) f_q \left( \frac{x}{\xi}, \mu; \alpha \right)
  $$

- We DON’T have the inverse function to go from cross sections to $\alpha$
Consider a simple scenario in 1D
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- Suppose we know \( f(x) \) but not its inverse.
Consider a simple scenario in 1D

- Suppose we know \( f(x) \) but not its inverse

- We can flip the graph to get the inverse

\[ f(x) \]
The key idea

We can parametrize the inverse given measurements of $f$ we can infer $x$ with the inverse.
The key idea

- We can parametrize the inverse

Given measurements of $f$, we can infer $x$ with the inverse.
The key idea

- We can parametrize the inverse
- Given measurements of \( f \) we can infer \( x \) with the inverse
The inverse mapper for global analysis

\[ \sigma_{P}^{-1} \]

\[ x_1, x_2, \ldots, x_N \quad \sigma_1, \sigma_2, \ldots, \sigma_N \quad \alpha_1, \alpha_2, \ldots, \alpha_M \]

\[ R^N \rightarrow R^M \]
The inverse mapper for global analysis

\[ \sigma^{-1}_P x \rightarrow R^M \]

Can we use Machine Learning?
Partnership with computer scientists

- M. Almaeen (ODU)
- Y. Awadh Alanazi (ODU)
- M. Houck (Davidson College)
- M. P. Kuchera (Davidson College)
- Y. Li (ODU)
- W. Melnitchouk (JLab)
- R. Ramanujan (Davidson College)
- NS (JLab)
- E. Tsitinidi (Davidson College)
ML prototypes

Tested and validated in toy DIS–like examples

How about real QCD analysis?
ML prototypes

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How about real QCD analysis?
ML prototypes

- Tested and validated in toy DIS–like examples
- How about real QCD analysis?
Application to unpolarized DIS
Application to unpolarized DIS

$Q^2$

$W^2 > 10 \text{ GeV}^2$

$\times_{bj}$

$g$

$u_V$

$d_V$

$\bar{d} - \bar{u}$

$s + \bar{s}$

$\bar{u} + d$

$\frac{1}{x}$
Application to unpolarized DIS
Application to unpolarized DIS

Proton DIS kinematics

Blobs $\propto \chi^2$

$\frac{\chi^2_{JAM}}{N_{\text{pts}}} = 1.25$

$\frac{\chi^2_{ML}}{N_{\text{pts}}} = 1.36$
Summary and outlook

- A new paradigm for QCD

+ simultaneous extraction of PDFs and FFs
+ boosts the SIDIS program to study hadron structure
+ the ultimate strategy for TMD and GPD physics
+ ripe for Machine Learning techniques
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