Modeling Nuclear PDFs with Neural Networks

[arXiv:1904.00018]

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Motivation

• Deep-inelastic scattering of leptons from nuclei cannot be described by free nucleon formalism (EMC effect), e.g.

DIS structure functions: $F_2^A \neq ZF_2^p + (A - Z)F_2^n$



• Mechanisms that originate nuclear effects not well understood

nPDFs from Global QCD Analyses

- Empirical determination of in-medium modifications to parton structure
- Relevant for interpretation of heavy ion collisions at RHIC and LHC
- Relies on collinear factorization formalism analogous to free proton fits

$$d\sigma^A(x,Q^2) \simeq \sum_f \int_x^{M_A/M} \frac{d\xi}{\xi} f^A(\frac{x}{\xi},Q^2) d\hat{\sigma}_f(\xi,Q^2)$$

• Scattering from nuclei treated incoherently from single bound nucleon

$$d\sigma^A(x,Q^2) \simeq Z d\sigma^{p/A} + (A-Z) d\sigma^{n/A}$$
$$d\sigma^{N/A}(x,Q^2) \simeq \sum_f \int_x^1 \frac{d\xi}{\xi} f^{N/A}(\frac{x}{\xi},Q^2) d\hat{\sigma}_f(\xi,Q^2)$$

• nPDFs are parameterized and fitted to global lepton-nucleus and hadron-nucleus scattering measurements

nNNPDF1.0 Analysis

- Includes all available neutral current DIS data from CERN, SLAC, and FNAL experiments
- Kinematic cuts:

 $W^2 > 12.5 \text{ GeV}^2$ $Q^2 > 3.5 \text{ GeV}^2$

• 451 total data points



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SLAU E-139	$^{4}\mathrm{He}/^{2}\mathrm{D}$	3
NMC 95, re.	$^{4}\mathrm{He}/^{2}\mathrm{D}$	13
NMC 95	$^{6}\mathrm{Li}/^{2}\mathrm{D}$	12
SLAC E-139	$^{9}\mathrm{Be}/^{2}\mathrm{D}$	3
NMC 96	$^{9}\mathrm{Be}/^{12}\mathrm{C}$	14
EMC 88, EMC 90	$^{12}{\rm C}/^{2}{\rm D}$	12
SLAC E-139	$^{12}{ m C}/^{2}{ m D}$	2
NMC 95, NMC 95, re.	$^{12}\mathrm{C}/^{2}\mathrm{D}$	26
FNAL E665	$^{12}\mathrm{C}/^{2}\mathrm{D}$	3
NMC 95, re.	$^{12}\mathrm{C}/^{6}\mathrm{Li}$	9
BCDMS 85	$^{14}\mathrm{N}/^{2}\mathrm{D}$	9
SLAC E-139	$^{27}\mathrm{Al}/^{2}\mathrm{D}$	3
NMC 96	$^{27}Al/^{12}C$	14
SLAC E-139	$^{40}\mathrm{Ca}/^{2}\mathrm{D}$	2
NMC 95, re.	$^{40}\mathrm{Ca}/^{2}\mathrm{D}$	12
EMC 90	$^{40}\mathrm{Ca}/^{2}\mathrm{D}$	3
FNAL E665	$^{40}\mathrm{Ca}/^{2}\mathrm{D}$	3
NMC 95, re.	$^{40}\mathrm{Ca}/^{6}\mathrm{Li}$	9
NMC 96	$^{40}{\rm Ca}/^{12}{\rm C}$	23
EMC 87	$^{56}\mathrm{Fe}/^{2}\mathrm{D}$	58
SLAC E-139	$^{56}\mathrm{Fe}/^{2}\mathrm{D}$	8
NMC 96	$^{56}{\rm Fe}/^{12}{\rm C}$	14
BCDMS 85, BCDMS 87	$^{56}\mathrm{Fe}/^{2}\mathrm{D}$	16
EMC 88, EMC 93	$^{64}\mathrm{Cu}/^{2}\mathrm{D}$	27
SLAC E-139	$^{108}\mathrm{Ag}/^{2}\mathrm{D}$	2
EMC 88	$^{119}\mathrm{Sn}/^{2}\mathrm{D}$	8
NMC 96, Q^2 dependence	$^{119}{\rm Sn}/^{12}{\rm C}$	119
FNAL E665	$^{131}{ m Xe}/^{2}{ m D}$	4
SLAC E-139	$^{197}\mathrm{Au}/^{2}\mathrm{D}$	3
FNAL E665	$^{208}\mathrm{Pb}/^{2}\mathrm{D}$	3
NMC 96	$^{208}{\rm Pb}/^{12}{\rm C}$	14
 Total		451

nNNPDF1.0 Analysis

- Single NN architecture with 3-25-3
- Input scale: $Q_0 = 1 \text{ GeV}$
- NN output multiplied by preprocessing

$$x\Sigma(x, Q_0, A) = x^{-\alpha_{\Sigma}}(1-x)^{\beta_{\sigma}} \xi_1^{(3)}(x, A)$$
$$xT_8(x, Q_0, A) = x^{-\alpha_{T_8}}(1-x)^{\beta_{T_8}} \xi_2^{(3)}(x, A)$$
$$xg(x, Q_0, A) = B_g x^{-\alpha_g}(1-x)^{\beta_g} \xi_3^{(3)}(x, A)$$



- Momentum sum rule: $\int_0^1 dx x (\Sigma(x, A) + g(x, A)) = 1 \rightarrow B_g = \frac{1 \int_0^1 dx x \Sigma(x, A)}{\int_0^1 dx x g(x, A)}$
- Parameters optimized by stochastic gradient descent in TensorFlow (open-source ML software library)

$$\Sigma \equiv \sum_{q} q^{+} = \sum_{q} q + \bar{q} \qquad T_{8} \equiv u^{+} + d^{+} - 2s^{+}$$

$$\chi^{2} \equiv \sum_{i,j=1}^{N_{\text{dat}}} \left(R_{i}^{(\text{exp})} - R_{i}^{(\text{th})}(\{f_{m}\}) \right) (\text{cov}_{t_{0}})_{ij}^{-1} \left(R_{j}^{(\text{exp})} - R_{j}^{(\text{th})}(\{f_{m}\}) \right)$$
$$+ \lambda \sum_{m=g,\Sigma,T_{8}} \sum_{l=1}^{N_{x}} \left(f_{m}(x_{l},Q_{0},A) - f_{m}^{(p+n)/2}(x_{l},Q_{0}) \right)^{2}$$

• Minimizing the cost function

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• Artificial data replicas — experimental data smeared by Gaussian

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- Theoretical predictions (functions of parameterized PDFs)

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- Artificial data replicas experimental data smeared by Gaussian
- Theoretical predictions (functions of parameterized PDFs)
- Covariance matrix encodes all statistical and systematic errors

$$(\operatorname{cov}_{t_0})_{ij}^{(\exp)} \equiv \left(\sigma_i^{(\operatorname{stat})} R_i^{(\exp)}\right)^2 \delta_{ij} + \left(\sum_{\alpha=1}^{N_{\operatorname{add}}} \sigma_{i,\alpha}^{(\operatorname{sys},a)} \sigma_{j,\alpha}^{(\operatorname{sys},a)} R_i^{(\exp)} R_j^{(\exp)}\right) + \sum_{\beta=1}^{N_{\operatorname{mult}}} \sigma_{i,\beta}^{(\operatorname{sys},m)} \sigma_{j,\beta}^{(\operatorname{sys},m)} R_i^{(\operatorname{th},0)} R_j^{(\operatorname{th},0)}\right)$$

<u>to prescription</u>: multiply correlated multiplicative uncertainties by central theory values from previous fit iteration

$$\chi^{2} \equiv \sum_{i,j=1}^{N_{\text{dat}}} \left(R_{i}^{(\text{exp})} - R_{i}^{(\text{th})}(\{f_{m}\}) \right) \left(\operatorname{cov}_{t_{0}} \right)_{ij}^{-1} \left(R_{j}^{(\text{exp})} - R_{j}^{(\text{th})}(\{f_{m}\}) \right)$$
$$+ \lambda \sum_{m=g,\Sigma,T_{8}} \sum_{l=1}^{N_{x}} \left(f_{m}(x_{l},Q_{0},A) - f_{m}^{(p+n)/2}(x_{l},Q_{0}) \right)^{2}$$

- Artificial data replicas experimental data smeared by Gaussian
- Theoretical predictions (functions of parameterized PDFs)
- Covariance matrix encodes all statistical and systematic errors
- Perform many fits to obtain representative MC sample distribution

$$E[\mathcal{O}(\vec{a})] = \sum_{k} w_k \mathcal{O}(\vec{a}_k) \qquad V[\mathcal{O}(\vec{a})] = \sum_{k} w_k (\mathcal{O}(\vec{a}_k) - E[\mathcal{O}])^2$$

$$\chi^{2} \equiv \sum_{i,j=1}^{N_{\text{dat}}} \left(R_{i}^{(\text{exp})} - R_{i}^{(\text{th})}(\{f_{m}\}) \right) (\text{cov}_{t_{0}})_{ij}^{-1} \left(R_{j}^{(\text{exp})} - R_{j}^{(\text{th})}(\{f_{m}\}) \right)$$
$$+ \lambda \sum_{m=g,\Sigma,T_{8}} \sum_{l=1}^{N_{x}} \left(f_{m}(x_{l},Q_{0},A) - f_{m}^{(p+n)/2}(x_{l},Q_{0}) \right)^{2}$$

- Boundary condition (imposed in the data region)
 - Free nucleon PDFs must be reproduced at A=1

$$f(x,Q,A=1) = \frac{1}{2} \left[f_p(x,Q^2) + f_n(x,Q^2) \right], \quad f = \Sigma, T_8, g$$

- NNPDF3.1 proton PDFs used as baseline
- Central values and *uncertainties* reproduced at minimization level "simultaneous" fit of proton and nuclear PDFs



- Uncertainties computed as 90% CL range
- Only linear combination of quark singlet and octet constrained by NC DIS

$$\Sigma = \sum_{i}^{n_f} (f_i + \bar{f}_i) = \sum_{i}^{n_f} f_i^+$$
$$T_8 = u^+ + d^+ - 2s^+$$



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NNPDF3.1 central values and uncertainties reproduced



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- NNPDF3.1 central values and uncertainties reproduced
- Increasing uncertainties with A — boundary condition effect

- Distributions normalized by respective proton boundary conditions
- EPPS16 and nCTEQ15 show 90% CL ranges based on Hessian method
- Significant differences in uncertainties



- Can test other boundary conditions e.g.
 NNPDF3.0+LHCb PDF set with smaller uncertainties at low x
- Remarkable impact of boundary condition choice — proton PDF constraints relevant for low-A nPDF extraction!



Impact of EIC

- Analysis of EIC pseudodata — extended kinematic coverage
- Two scenarios: low
 energy (5 GeV) vs high
 energy (20 GeV) electron
 beam



Scenario	A	E_e	E_A/A	$Q_{ m max}^2$	x_{\min}	$N_{\rm dat}$	
eRHIC_5x50C	12	$5 { m GeV}$	$50 { m GeV}$	$440 \ {\rm GeV^2}$	0.003	50	
$eRHIC_5x75C$	12	$5~{ m GeV}$	$75 {\rm GeV}$	$440 \ {\rm GeV^2}$	0.002	57	
$eRHIC_5x100C$	12	$5~{ m GeV}$	$100 { m ~GeV}$	$780 \ { m GeV^2}$	0.001	64	
$eRHIC_5x50Au$	197	$5~{ m GeV}$	$50 { m GeV}$	$440 \ {\rm GeV^2}$	0.003	50	
$eRHIC_5x75Au$	197	$5~{ m GeV}$	$75 {\rm GeV}$	$440 \ {\rm GeV^2}$	0.002	57	
$eRHIC_5x100Au$	197	$5~{ m GeV}$	$100~{\rm GeV}$	$780 \ { m GeV^2}$	0.001	64	
eRHIC_20x50C	12	$20 { m GeV}$	$50 { m GeV}$	$780 \ { m GeV^2}$	0.0008	75	
$eRHIC_20x75C$	12	$20 { m GeV}$	$75 {\rm GeV}$	$780 \ { m GeV^2}$	0.0005	79	
eRHIC_20x100C	12	$20 { m GeV}$	$100 { m ~GeV}$	$780 \ { m GeV^2}$	0.0003	82	
eRHIC_20x50Au	197	$20 { m GeV}$	$50 { m GeV}$	$780 \ { m GeV^2}$	0.0008	75	
eRHIC_20x75Au	197	$20 { m GeV}$	$75 {\rm GeV}$	$780 \ { m GeV^2}$	0.0005	79	
eRHIC_20x100Au	197	$20 { m GeV}$	$100 { m ~GeV}$	$780 \ { m GeV^2}$	0.0003	82	

- Pseudodata constructed with nNNPDF1.0 results
- Uncertainty projections from E.C. Aschenaur et. al. [arXiv:1708.05654]

Impact of EIC



• Significant reduction of uncertainties for high-A, low-*x* — particularly for higher energy option

Towards nNNPDF1.5

- Experimental data: CC DIS + W/Z production at LHC
- Theoretical improvements: new BC, positivity, valence sum rules
- Closure tests successful! — full analysis to be completed soon



Summary and Outlook

- Machine learning + Monte Carlo methods are important for robust extractions of nPDFs and their uncertainties
- Methodology improvements in nPDF analysis
 - Neural network optimized by SGD in TensorFlow
- Highlights from first Monte Carlo nPDF fit
 - Significant impact of A=1 boundary condition for low-A nuclei
 - High energy EIC option constrains PDFs down to $x \sim 10^{-4}$
- Upcoming nNNPDF1.5 analysis (completing very soon!)
 - Experimental data: CC DIS + W/Z production
 - Theoretical improvements: new BC, positivity, valence sum rules