





# Al-driven evaluation of $\pi^+ n$ electroproduction cross sections and structure functions from the CLAS data

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## Objectives for Al-driven studies of the $\pi^+ n$ electroproduction data.

• Explore AI capabilities to evaluate two-fold differential  $\pi^+ n$  electroproduction cross section and to provide interpolation/extrapolation on a user-defined kinematic grid. Assess accuracy of data prediction.

• Explore AI capabilities to establish the dynamics of  $\pi^+ n$  electroproduction reaction from the studies of multi-dimensional correlations in the measured observables, in particular, the ability to reproduce the  $\varphi$ -dependence (see Eq in slide #4) for an algorithm with no prior constrains.

• Explore AI capabilities to reproduce two-fold differential  $\pi^+ n$  electroproduction cross section in the areas of small or zero acceptance.

#### Dataset from CLAS experiment

The measured cross sections are stored in the CLAS Physics Database created in collaboration between Hall B at Jefferson Lab and SINP MSU

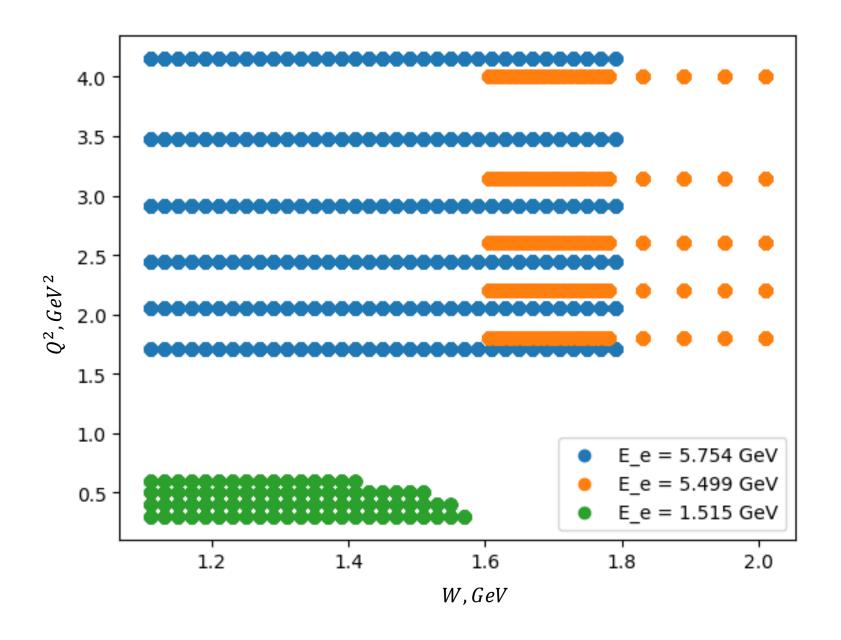
https://clas.sinp.msu.ru/cgi-bin/jlab/db.cgi

Beam energies for the data included in AI/ML studies:

 $E, GeV \in \{5.754, 5.499, 1.515\}$ 

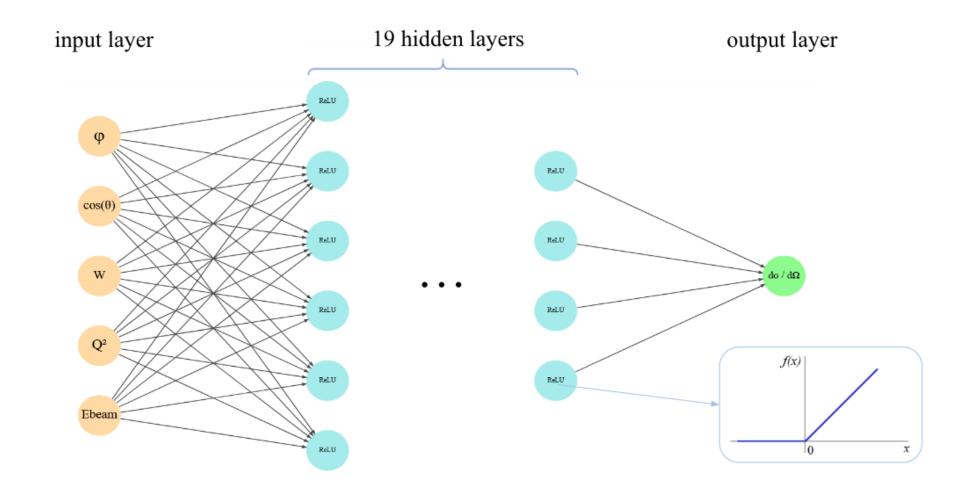
	Ebeam	W	Q2	cos_theta	phi	dsigma_dOmega	error	id
0	1.515	1.11	0.3	0.991445	0.261799	15.3700	5.264366	E8M1
1	1.515	1.11	0.3	0.991445	0.785398	4.5110	1.743136	E8M1
2	1.515	1.11	0.3	0.991445	1.308997	4.4780	1.611260	E8M1
3	1.515	1.11	0.3	0.991445	1.832596	5.1360	1.523529	E8M1
4	1.515	1.11	0.3	0.991445	2.356194	5.0780	1.219442	E8M1
98022	5.499	2.01	4.0	0.975000	3.730641	0.1012	0.043165	E141M160
98023	5.499	2.01	4.0	0.975000	3.992441	0.1199	0.076638	E141M160
98024	5.499	2.01	4.0	0.975000	4.646939	0.1578	0.095391	E141M160
98025	5.499	2.01	4.0	0.975000	4.777839	0.2346	0.158557	E141M160
98026	5.499	2.01	4.0	0.975000	6.086836	0.1250	0.077753	E141M160

### Kinematic coverage



## Network architecture

Rumelhart, D., Hinton, G. & Williams, R. Learning representations by back-propagating errors. *Nature* 323, 533–536 (1986). https://doi.org/10.1038/323533a0



Validation – baseline: Quality of the training

$$MAE = \frac{1}{N} \sum_{i}^{i=N} |y_i^{experimental} - \hat{y_i}^{predicted}|$$

Average value and error of cross sections (experimental):

$$AVG(d\sigma/d\Omega) = 1.158 \pm 0.2 mcb/sr$$

Mean absolute error of Al algorithm of cross-section prediction on a test samples:

$$MAE(d\sigma/d\Omega) \cong 0.08 mcb/sr$$

MAE error is smaller than average error of differential cross-section. Good quality of training!

## Validation

$$E = 5.754 \ GeV; Q^2 = 2.915 \ GeV^2$$
  
1<sup>st</sup> resonance region

## E=5.754~GeV; $Q^2=2.915~GeV^2$ - 1st resonance maximum

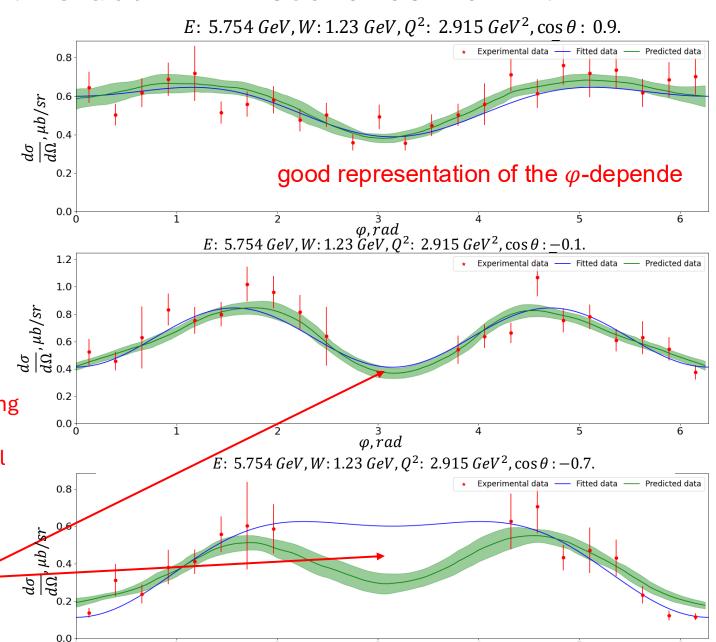
Red dots with error bars – experimental data

**Blue line** – fit of the experimental data by Eq. in slide #4

**Green line** - Neural network predictions with uncertainties shown by green areas obtained from bootstrap

Al algorithm is capable of determining  $\varphi$ -depende of  $\pi^+ n$  differential cross sections from the multi-dimensional data analysis

Al algorithm provides predictions for  $\pi^+ n$  differential cross sections within  $\varphi$ -ranges where the data are not available



 $\varphi$ , rad

## $E = 5.754 \ GeV$ ; $Q^2 = 2.915 \ GeV^2$ - structure functions

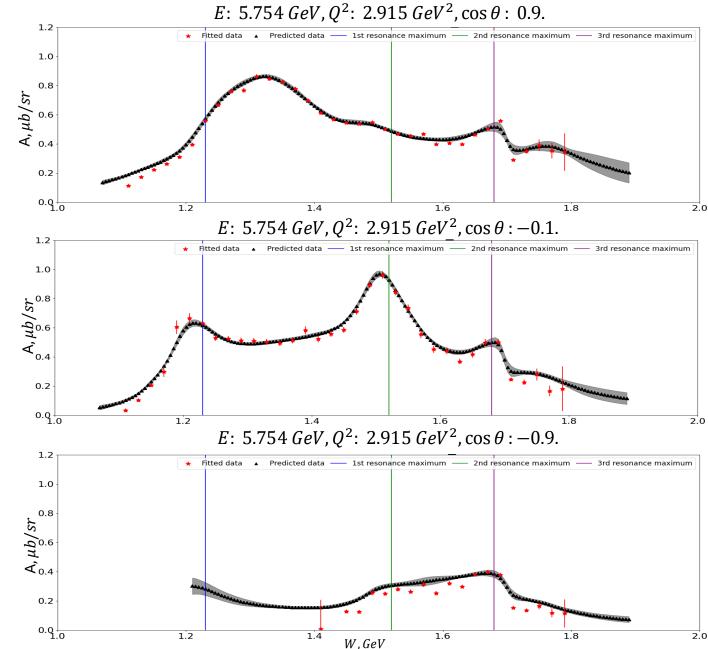
Red dots with error bars – structure functions from the experimental data fit.

Black line – predicted structure function obtained from the moments of the predicted within AI/ML cross sections with uncertainties from bootstrap

Blue line – the center of the 1<sup>st</sup> resonance region (W=1.23 GeV)

**Green line** – the center of the 2<sup>nd</sup> resonance region (W=1.52 GeV)

Purple line – the center of  $3^{rd}$  resonance region for  $\pi^+ n$  (W=1.68 GeV)



## Replica method

- 1. Fix experimental dataset  $o DS_{exp}^{j,k}$  , where  $DS_{exp}^{j,k} = DS_{exp}^{j-1,k} \cup \frac{d\sigma^k}{d\Omega_{PX}}$
- 2. Train a model  $M_{repl.gen.}$  (on  $DS_{exp}^{j,k}$ ) and make predictions  $\rightarrow \frac{d\sigma^k}{d\Omega_{repl.gen.}}$
- 3. Generate **100** pseudodata vectors of cross-sections  $\frac{d\sigma^{i,k}}{d\Omega_{renl}}$  via Gaussian blurring technique with params:

$$\mu^k=rac{d\sigma^k}{d\Omega_{repl,qen.}}$$
 ,  $\sigma^k=rac{d\sigma^k}{d\Omega_{error}}$  , where  $rac{d\sigma^k}{d\Omega_{error}}\subset DS_{exp}^{j,k}$ 

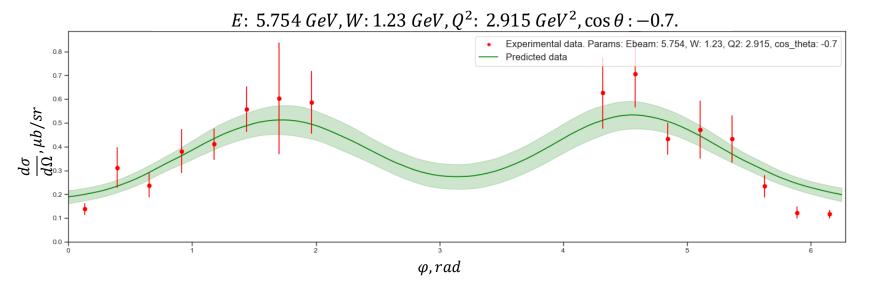
- $\mu^k = rac{d\sigma^k}{d\Omega_{repl.gen.}}$ ,  $\sigma^k = rac{d\sigma^k}{d\Omega_{error}}$ , where  $rac{d\sigma^k}{d\Omega_{error}} \subset DS_{exp}^{j,k}$ 4. Train **100** models  $M_{repl}^i$  on corresponding  $DS_{repl}^{i,j,k} = DS_{exp}^{i,j-1,k} \cup rac{d\sigma^{i,k}}{d\Omega_{repl}}$ 
  - and make **100** cross-sections prediction vectors  $\frac{d\sigma^{i,k}}{d\Omega_{repl.preds.}}$
- 5. Take standard deviation  $\sigma$  and average  $\mu$  from  $\frac{d\sigma^{i,k}}{d\Omega_{repl.preds.}}$  compare with  $\frac{d\sigma^k}{d\Omega_{exp}}$ .

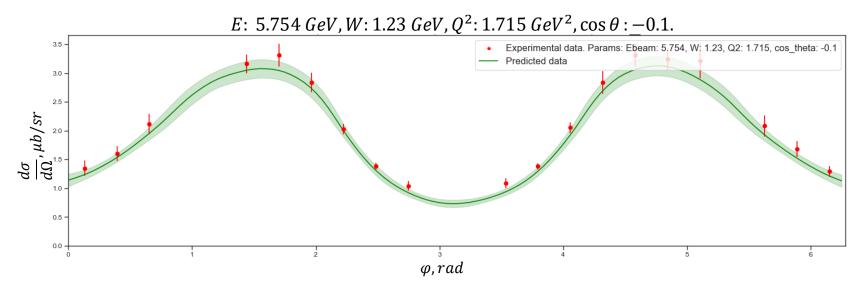
## Replicas prediction

experimental data								replicas generator	or replicas			replicas predictions		
id	Ebeam W	1	Q2	cos_theta	phi	$d\sigma/d\Omega$	error	$d\sigma/d\Omega_prediction$	$d\sigma/d\Omega$ _replica_1		$d\sigma/d\Omega$ _replica_100	$d\sigma/d\Omega$ _replica_prediction_1		$d\sigma/d\Omega$ _replica_prediction_100
C	1.515	1.11	0.3	0.99145	0.268998	15.37	5.26	15.17	15.208		15.081	15.133		15.16
1	1.515	1.11	0.3	0.99145	0.785623	4.532	1.743	4.331	4.337		4.25	4.342		4.276
2	1.515	1.11	0.3	0.99145	1.308992	4.478	1.622	4.538	4.596		4.456	4.53		4.502
3	1.515	1.11	0.3	0.99145	1.861923	5.136	1.53	5.333	5.395		5.291	5.316		5.375
4	1.515	1.11	0.3	0.99145	2.356194	5.078	1.22	5.571	5.576		5.514	5.598		5.564
98024	5.754	1.53	1.715	0.7	0.3927	1.304	0.042	1.337	1.337		1.248	1.288		1.286
98025	5.754	1.53	1.715	0.7	0.6544	1.424	0.043	1.464	1.539		1.37	1.374		1.463
98026	5.754	1.53	1.715	0.7	0.9162	1.605	0.063	1.666	1.721		1.652	1.718		1.738
98027	5.754	1.53	1.715	0.7	1.178	1.975	0.111	1.907	1.936		1.877	1.927		1.91

$$\frac{d\sigma}{d\Omega_{diff_i}} = \frac{\frac{d\sigma}{d\Omega_{prediction}} - \frac{d\sigma}{d\Omega_{replica\_prediction_i}}}{\frac{d\sigma}{d\Omega_{prediction}}}$$

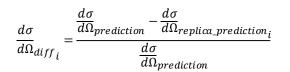
## Step 3 – replicas prediction validation

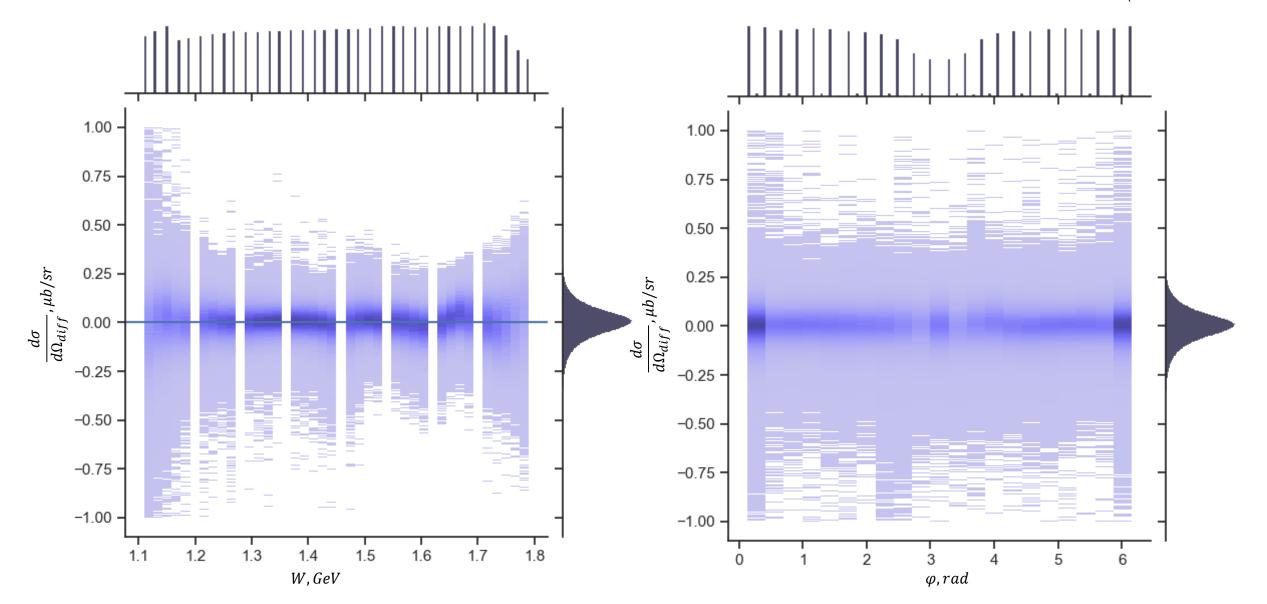




For each point in phase space, 100 predictions were made on 100 replica models and the green area represents 1 standard deviation over these 100 predictions for each point.

## Replicas prediction validation

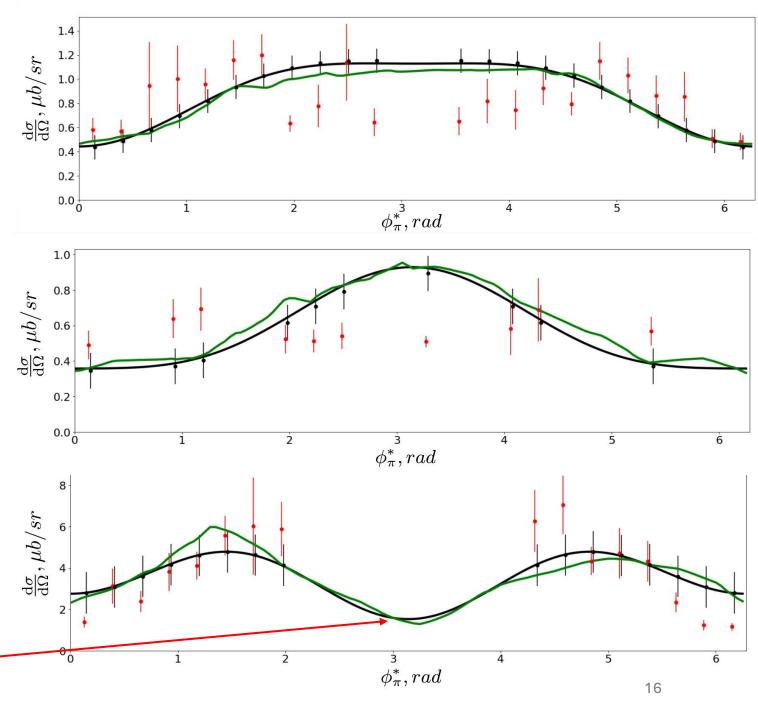




## MAID comparisons

## Replicas prediction validation

- The model  $\pi^+ n$  cross sections were computed from MAID07 within the entire kinematic area (black lines)
- Al was trained on the grid, where CLAS cross sections (red data points) are available, to reproduce the MAID07 quasi-data (black points). The Al estimates (green lines) are compared with MAID07 results within the entire reaction phase space.
- Al algorithm well reproduce the MAID cross sections within areas of zero acceptance



### Conclusions

- The Al-driven approach for evaluations of the  $\pi^+ n$  differential cross sections and structure functions from the data measured with CLAS has been developed. The approach reproduces the available experimental results with good accuracy and offers predictions for  $\pi^+ n$  electroproduction observables within the area of 1.1~GeV < W < 2~GeV and  $0.5~GeV^2 < Q^2 < 4~GeV^2$ .
- All algorithms establish the  $\varphi$ -dependence of  $\pi^+ n$  cross sections from multi-dimensional data analysis without prior knowledge.
- All algorithms allow us to evaluate  $\pi^+ n$  differential cross section within the reaction phase space where the experimental data are not available (in particular, in the areas of zero acceptance) from accounting for multi-dimensional correlations.
- The structure functions for  $\pi^+ n$  electroproduction have been deduced from the CLAS data at  $1.1~GeV < W < 2~GeV~and~0.5~GeV^2 < Q^2 < 4~GeV^2$

## Thank you for your attention!