Maxime DEFURNE presents:

Discussion about GPD experiments

Courtesy to:

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Understanding the pi0 electroproduction

- Pi0-electroproduction is a beautiful example of higher-order contributions dominance in Jlab kinematical domain.

\[
\frac{d\sigma}{dt} = \frac{d\sigma_T}{dt} + \varepsilon \frac{d\sigma_L}{dt} + \frac{d\sigma_{TL}}{dt} \sqrt{2\varepsilon (1 + \varepsilon)} \cos(\Phi) + \frac{d\sigma_{TT}}{dt} \varepsilon \cos(2\Phi)
\]

- For pi0, the longitudinal term is the leading-twist term. It was expected to be small. But the cross section was found to be a order of magnitude higher than expected.

- Although unexpectedly large, the phi-modulation of the cross section was providing already a wealth of information: A large transverse contribution.
Vector meson electroproduction is as interested as pseudo-scalar mesons.

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Through \( \gamma^*_L p \to p \phi_L \), we access the gluon GPDs.

\[ \frac{d\sigma_L}{dt} = \frac{\alpha_{em}}{Q^2} \frac{x_B^2}{1 - x_B} \left[ (1 - \xi^2)|\langle H_g \rangle|^2 + \text{terms in } \langle E_g \rangle \right], \]

The conservation of helicity in the s-channel is usually assume but there are experimental evidence that it is not valid. Exemple: \( \omega \)-electroproduction (SCHC not valid at low-t for \( Q^2 \) as high as 4.5 GeV^2)

Only a Rosenbluth separation can provide a clean access to GPDs (if we want to do multi-channel GPD extraction... Brace yourself.)

The t-slope is not everything... only a salesman argument? especially if you want to plug gluon GPDs in DVCS to access pure quark info.
What about deeply virtual Compton scattering?

- The same decomposition can be applied to DVCS cross section (I insist on the DVCS, it is not photon electroproduction)

\[
\begin{align*}
C_{0,\text{unp}}^{\text{VCS}} &= 2 - 2y + y^2 + \frac{\epsilon^2}{2} y^2 \left( \mathcal{F}_{++}, \mathcal{F}^*_{++} \big| \mathcal{F}^{*+}_{--}, \mathcal{F}^{*-}_{++} \big) \right) + 8 \frac{1 - y - \frac{\epsilon^2}{4} y^2}{1 + \epsilon^2} C_{\text{unp}}^{\text{VCS}} (\mathcal{F}_0^+, \mathcal{F}^*_0^+) , \\
C_{1,\text{unp}}^{\text{VCS}} &= 4\sqrt{2} \sqrt{1 - y - \frac{\epsilon^2}{4} y^2} \left\{ \begin{array}{l} 2 - y \\ -\lambda y \sqrt{1 + \epsilon^2} \end{array} \right\} \{ \Re \} - \lambda y \sqrt{1 + \epsilon^2} \{ \Im \} C_{\text{unp}}^{\text{VCS}} (\mathcal{F}_{0+}^+, \mathcal{F}^*_{++}, \mathcal{F}^{*-}_{--} , \mathcal{F}^{*+}_{--}) , \\
C_{2,\text{unp}}^{\text{VCS}} &= 8 \frac{1 - y - \frac{\epsilon^2}{4} y^2}{1 + \epsilon^2} \Re C_{\text{unp}}^{\text{VCS}} (\mathcal{F}_{--}^+, \mathcal{F}^{*+}_{++}) .
\end{align*}
\]  

(37)  

(38)  

(39)

- A wealth of leading-twist/leading-order studies while most (all?) DVMP channels exhibit significant higher order contributions. Why so? **DVCS hidden under BH and interference term!!**

Big Bethe-Heitler!  
Big unknown Interference  
Big?? unknown DVCS
What do we know about photon electroproduction?

▶ To sell DVCS studies, Bethe-Heitler is very useful. The interference (at LT/LO) gives you a very convenient access to real and imaginary part of CFFs. Are we allowed to stay at LT/LO? => The DVCS2 contribution should not show any phi-modulation. (What about EIC? Only scaling to look at gluon? No chance for phi-modulation?)

▶ But, looking at most cross sections, it is dominated by Bethe-Heitler. You cannot do this visual inspection of the DVCS cross section as you do with DVMP.

▶ So far, there was/will be attempt to perform Rosenbluth separation. For the 2010 DVCS experiment in Hall A, by lowering the beam energies, the Bethe-Heitler exploded.

▶ Non-unique DVCS/Interference separation... With attempt to use the kinematic power corrections, NLO and/or longitudinal contributions are needed.
How to know what is in photon electroproduction?

- The **cleanest way** to separate Interference and DVCS is to use positrons.
- If we want to use positrons, we want to be sensitive to interference and so we need to have enough Bethe-Heitler.
- 0.5 uA of unpolarized positrons in well chosen kinematics would definitely unravel DVCS^2 with enough accuracy to guide us on what we are looking at. (my instinct).
- **More accurate statement** can be easily derived **within a few post-doc days thanks to PARTONS!!**

- Using the 12 GeV beam at a few 6-GeV kinematics point (xB=0.36 and Q^2=2 GeV^2), it would allow a super Rosenbluth separation.
- For this point, **Bethe-Heitler is greatly suppressed** compared to 6-GeV beam. We can distinguish between the different scenarii.
What is then a good DVCS measurement?

I would define a good DVCS measurement as:
- A measurement maximizing the gain about GPD information
- For the lesser experimental cost.

**Problem: How to measure the gain in GPD-information from a measurement:**

- I am very glad PARTONS is available!!! (Just need money for Post-doc/Student now)
- Until then, from my past experience, I learnt a set of rules (to be discussed):
  - Aim at kinematics not covered yet, or poorly constrained. (go Jlab12, go COMPASS, go EIC!!)

  - *Not too much Bethe-Heitler* contribution for unpolarized cross sections.
    (Where too much Bethe-Heitler, *can you tell much without the unpolarized cross sections?*)

  - Since we mostly work on CFF for the moment, try to cover a complete phi-acceptance.
    (Sometimes you have to make a choice between statistics and acceptance.)
    (What about when you work at GPD-level?)
    (With multi-channel analysis?)

These questions are of tremendous importance, at least for Jefferson Lab, for which we have flexibility on the experimental configuration:
- For CLAS12, Torus polarity change the statistics and acceptance. (Phi vs photon electroproduction)
- Still for CLAS12, trade-off between luminosity and detector proximity of the beamline.
Towards the future…

Figure 1: Layout of CEBAF.
Artificial intelligence and caution

- **Machine learning** has invaded our daily life... especially under the form of deep neural networks:
  - **Classification**: Dog/cats, cancer diagnosis,...
  - **Fitting, modeling**: Flexible enough to take a form you don’t know

- We do not want to do more than cat/dog classification but we need to prove that we understand the underlying logic of any machine learning analysis, characterize its performances.
  => Need to understand artificial intelligence!!

- The goal is to apply Machine learning algorithms with a constrain about its interpretability. It is easier to understand how to use these tools on a well-known physics case.

✔ Linear regression \( y = AX + b \)

✔ Decision trees (Human)

\[
\text{IF } x_1 > 2.7 \text{ AND } x_2 < -4.3 \\
\text{THEN } y = \text{signal}
\]

≅ Boosted decision trees \( y = \text{vote among trees} \)

✘ Neural networks \( y = \text{complex non-linear function of inputs} \)
We will try to understand Machine Learning on DVCS event selection with its well-known pi0 contamination.

Example of a DVCS event in CLAS12:

Depending on kinematics and torus polarity, the proton can be sent in DCs, and/or the photon in ECAL.

A lot of detectors and different configurations for a DVCS events: a good case to study ML.
You start from data (3-momentum, pid, vertices, detector signals) and you want to train a ML model.

If deep enough, a **NN will be able to build non-linear combinations** of inputs... But Boosted decision trees and most of **interpretable methods do not have this flexibility**. So a first step is to build good and sound features (combinations of data used as inputs for the model).

```plaintext
<start> ::= <E> | <A> | <F>
<E> ::= <E> + <E> | <E> - <E> | <E> * <F>
| <E> / <F> | sqrt(<E2>) | <termE>
<A> ::= <A> + <A> | <A> - <A> | acos(<F>)
| asin(<F>) | atan(<F>) | <termA>
<F> ::= <F> + <F> | <F> - <F> | <F> * <F>
| <F> / <F> | <E> / <E> | <A> / <A>
| cos(<A>) | sin(<A>) | tan(<A>)
| <termF>
<E2> ::= <E2> + <E2> | <E2> - <E2>
| <E> * <E> | <E2> * <F> | <E2> / <F>
| square(<E>) | <termE2>
```
Genetic algorithms to construct high-level feature

- We start from an initial population of trees and produce out of them “offsprings” with mutation/cross-over.

- Genetic programming with grammar rules is not new methods.

- To select individuals for the next generation, “survival of the fittest” among offspring and initial populations by checking improvement of a classifier score due to the newly constructed feature added to the initial sets of inputs.
Prospect concerning feature construction

- Comparison between physicist inputs and constructed features: Learning from Data-driven classifier
  - Variables d’exclusivité de Guillaume
    - $M[ep\rightarrow ep\gamma]$ +0.77%
    - $M[ep\rightarrow epX]$ +0.23%
    - Photon energy +0.23%
    - Cone angle +1.69%
    - Photon energy + cone angle +1.75%
    - All of the above +2.04%
  
  - Variables d’exclusivité produite par Noélie
    - $M_p + (p_e + p_p + p_{\gamma_1})_z$ +2%
    - $||p_e + p_p + p_{\gamma_1}||$ +2%

- Physicist can learn from feature construction!

- Some case-by-case optimization:
  - Cartesian $\neq$ Spherical.
  - Evaluator classifier = analysis classifier.
  - Should we remove from the initial set of inputs the correlated ones with the new feature?

- This feature construction algorithm has been run over the entire CLAS12 phase space:
  - Vectorial $+1.87 \pm 0.24\%$
  - Spherical $+0.98 \pm 0.28\%$
  - Cartesian $+1.93 \pm 0.09\%$

- We might want to construct features/inputs for each possible configuration (depending where protons and photons are.)
How to train properly any classifier?

- So far, we use Boosted Decision Trees and Neural Networks. They are trained with a simulation of DVCS and pi0 events.

- If you include “dynamics” in the training samples, the algorithm tends to learn the topological distributions instead of inferring “rules/laws”.

- Working with data analysts, they have no elegance in analyzing data... Brute force approach. But smaller Neural Networks or trees trained on dedicated part of phase space were more efficient and more interpretable.
  How many Neural Networks or interpretable algorithms do we need to cover the phase space? Most likely one for negative inbending and a second one for negative outbending.
It is **not a new problem**. Even classical analyses face the challenge of confronting MC to reality for acceptance computation,…

There are two ways to proceed:

- **The transferred simulation is preferred** because it can be used for any training afterwards. Nevertheless it is the way that costs time. It will be one of the main work for this year.

- A **large source of systematics is associated to the MC simulation**. And, considering the **statistical accuracy of JLab12**, we must gain as much as we can on all front. (Radiative corrections?)
Physicist versus Machine

- In the end, I am a physicist, I just want the **most accurate results** (best statistical and systematic uncertainties.)

- The goal is to **quantify the performances of the three approaches on 3-particle and 2-particle coincidence**.

- Not sure DVCS and pi0 is the best case to demonstrate ML performances, but it is a start to **understand how ML works before going to more exotic channels**.