# A Machine Learning approach for DVCS identification without proton detection

Juan Sebastian Alvarado IJCLab - Orsay

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## Introduction

- **2** Analysis of  $ep \rightarrow e\gamma p$ 
  - Data selection
  - Model training
  - Background substraction
  - BSA

#### **3** Analysis of $ep \rightarrow e\gamma(p)$

- Data selection
- Model training
- Background subtraction
- BSA

#### 4 Conclusions

## Introduction

In principle, the measurement of only an electron and a photon is enough to reconstruct a DVCS event. We aim for DVCS event reconstruction without requiring final proton information. **Advantages (with respect to**  $ep\gamma$  **detection):** 

- □ Improves GPD studies at small -t.
- □ Higher statistics, hence more precise BSA measurements or smaller bins.
- □ Helpful for experiments that do not consider proton detection.

#### Difficulties:

- □ The  $ep\gamma$  final state includes background contributions from the whole Deep Inelastic Scattering (DIS) spectra.
- Reduced options for cuts:
  - □ Only one exclusivity variable: Missing mass of  $ep \rightarrow e\gamma$ .

Therefore, we need a method that ensures DVCS identification: Machine Learning

We test the ML approach on experimental data:

- 1. Validation of the method when we include the proton information.
- 2. Application to the case without proton information.

## $ep \rightarrow e\gamma p$ : Data selection

#### Analyzed data set

- fall2018 RG-A data.
- Inbending and outbending torus configuration

#### Kinematic window:

- $\Box W > 2 \text{ GeV},$
- $\Box$   $Q^2>1~{
  m GeV^2}$  ,
- $\hfill \ensuremath{\square}$   $\ensuremath{\mathbf{q}'}\xspace > 2$  GeV (photon),
- $\hfill\square\hfill {\bf k}'>1$  GeV (electron),
- $\label{eq:prod} \textbf{p}' > 0.3 \ \text{GeV} \ (\text{nucleon}).$



#### **Exclusivity cuts:**

We reconstruct  $\phi$  and t in two ways:

- 1. Using  $\gamma *$  and the outgoing photon  $\gamma : \Rightarrow \phi(\gamma)$
- 2. Using  $\gamma *$  and the recoil proton  $p: \Rightarrow \phi(p')$

$$\Box \ \Delta \phi = |\phi(p') - \phi(\gamma)| < 2^\circ$$
,

$$\Box \ \Delta t = |t(p') - t(\gamma)| < 2 \text{ GeV}^2,$$

 $\Box \ \mathbf{P}_{miss} < 1 \ \mathrm{GeV}.$ 

#### **Event selection:**

- No restriction on the number of particles in the event or detection topology.
- □ If multiple *e*,  $\gamma$  or *p* detections, we select the set (*e*,  $\gamma$ , *p*) that minimizes the missing mass of the process *ep* → *ep* $\gamma$

# $ep \rightarrow e\gamma p$ : Model training - Inbending torus The main contamination channel is $ep \rightarrow ep\pi^0 \rightarrow ep\gamma(\gamma)$ .



## $ep \rightarrow e\gamma p$ : BDT - Inbending torus

A Boosted Decision Tree (BDT) was trained to classify the events.

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- $\Box \text{ Discriminating variables: } \{M^2_{ep\gamma}, M^2_{e\gamma}, \Delta\phi, \Delta t, \theta_{\gamma X}\}.$
- □ Simulated DVCS as signal.
- $\hfill\square$  Simulated  $\pi^0$  events, reconstructed as DVCS, as background.
- **Training is done on each**  $(Q^2, x_B, t)$  bin.



## $ep \rightarrow e\gamma p$ : BDT - Inbending torus

We extract a dataset with DVCS $\sim$  94.5% and DVMP $\sim$  5.5%.



#### Histograms are normalized to 1.

## $ep \rightarrow e\gamma p$ : Background subtraction

To estimate and remove the residual background on each  $(t, Q^2, x_B, \phi)$  bin and helicity state we use two methods:

#### Method 1:

Let us define:

- $\square n_{MC/Data}^{1\gamma} = \text{Number of} \\ \text{simulated } \pi^0 \text{ events that pass} \\ \text{the DVCS analysis.} \\$
- □  $n_{MC/Data}^{2\gamma}$  = Number of simulated  $\pi^0$  events that are reconstructed.

The contamination is then:

$$n_{Data}^{1\gamma} = \left(\frac{n_{MC}^{1\gamma}}{n_{MC}^{2\gamma}}\right) n_{Data}^{2\gamma}.$$

#### Method 2:

- **1.** Reconstruct  $\pi^0$  events.
- 2. For each  $\pi^0$ , generate 1500 decays.
- 3. If the event pass the DVCS analysis with any photon, fill histograms.
- 4. If the event pass the DVMP analysis, increment  $n_{MC}^{2\gamma}$  by the reconstruction efficiency.
- 5. At the end of the decays, DVCS events are normalized by  $1/n_{MC}^{2\gamma}$ .

### $ep \rightarrow e\gamma p$ : Background subtraction

#### About the background subtraction:

- $\hfill\square$  The final estimation is given by the average of the two.
- □ Error on the estimation is given by the difference of each method from the average.

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#### About the BSA measurements:

□ Identical  $(t, Q^2, x_B)$  binning of the RG-A analysis note (64 in total) used for this analysis.

#### Systematic uncertainties have been estimated.



# $ep \rightarrow e\gamma p$ : **BSA: benchmark measurements**



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## $ep \rightarrow e\gamma p$ : **BSA**

All in all, we saw that:

- □ The inbending dataset can still provide an important contribution in the  $Q^2 < 1.8$  GeV<sup>2</sup> region.
- Inbending and outbending configuration measurements are compatible.
- □ The background contamination after BDT is small.
- Both background subtraction methods give similar results.
- The BDT classification boost the statistics importantly.



# $ep \rightarrow e\gamma(p)$ : Data selection

#### Kinematic window:

We apply the same kinematic restrictions:

- $\label{eq:W} \begin{array}{ll} \square & W > 2 \mbox{ GeV}, \\ \square & Q^2 > 1 \mbox{ GeV}^2 \ , \\ \square & {\bf q}' > 2 \mbox{ GeV (photon)}, \\ \square & {\bf k}' > 1 \mbox{ GeV (electron)}. \end{array}$
- $\Box$   $-rac{t}{Q^2} < 1$ ,

#### **Exclusivity cuts:**

However, our exclusivity cuts are no longer useful.

#### **Event selection**

- Only analyze events with 1 or 2 photons.
- The event is selected by taking the most energetic photon and electron.

#### **BDT** training:

- □ Training using experimental data:
  - (Background) signal are the events that (do not) pass the analysis with proton information.
- □ Discriminating variables:  $\{M_{e\gamma X}^2, M_{eX}^2, t\}$ .

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# $ep ightarrow e\gamma(p)$ : Model training - Inbending

#### The following variables are used for training.



**Figure:** Missing masses  $M_{e\gamma X}^2$ ,  $M_{eX}^2$  and *t*, normalized to 1, for raw data (red), training DVCS dataset (black) and training  $\pi^0$  dataset (blue).

#### Histograms are normalized to 1.



# $ep \rightarrow e\gamma(p)$ : Background subtraction

Without proton detection, the  $e\gamma$  final state receives contributions from a large set of processes. However:

1. Photon emission comes mainly neutral meson decays, being  $\pi^{\rm 0}$  the dominant one.

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- 1. Photon emission comes mainly neutral meson decays, being  $\pi^0$  the dominant one.
- 2. The contamination channel is now **inclusive**  $\pi^0$  production.
- 3. Both background subtraction methods are valid for such case, and it only depends on a good  $\pi^0$  reconstruction.



# $ep \rightarrow e\gamma(p)$ : Comparison with $e\gamma p$ detection

After BDT cut and background subtraction, there is an important increase on statistics



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**Figure:** Kinematic variables for the analysis with proton (red) and without proton (blue) information.

# $ep \rightarrow e\gamma(p): \text{BSA} - \text{Benchmark measurements}$ Bin 26: 1.8 < $Q^2(\text{GeV}^2)$ < 2.4, 0.16 < $x_B$ < 0.26, $-t(\text{GeV}^2)$ < 0.2 Inbending Outbending

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## Systematic Errors

It will be done by comparing the BSA amplitude when the analysis is done with some modifications.

□ Due to the exclusivity cuts:

□ Re-do the full analysis using slightly tighter selection cuts □  $|\Delta t|$ ,  $|\Delta \phi|$ ,  $P_{miss}$ . 16/19

Due to the beam polarization uncertainty

 $\Box\,$  Estimated to be  $\sim 5\%$  of the BSA.

Due to the choice of BDT cut.

□ Re-do the analysis using a different BDT cut.

□ Due to the background subtraction.

$$\Box \ \delta A = \frac{A^{raw} - A_{\pi^0}}{(1-f)^2} \delta f$$

□ *f* is the contamination before subtraction,  $A_{\pi^0} \approx 0.05$  and  $\delta f$  is the estimation difference of both methods.

□ Total error as the quadratic sum of components.

### **Systematic Errors**

## **Bin 26:** $1.8 < Q^2(\text{GeV}^2) < 2.4, \ 0.16 < x_B < 0.26, \ -t(\text{GeV}^2) < 0.2$



- Background subtraction methods agree.
- □ Systematics have decreased.

## Conclusions

- Boosted decision trees presents an alternative for channel selection on an event-by-event basis.
- □ When the final proton is included:
  - DVCS exclusivity variables have enough separation power to allow DVCS and Deep Exclusive \u03c0<sup>0</sup> Production identification in an efficient way.

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- □ When the final proton information is ignored:
  - □ There is a wider phase space towards the small *t* region.
  - There is a boost on statistics leading to more precise BSA measurements.
- $\hfill Without any restriction on the detection topology we extract datasets of <math display="inline">\sim$  95% DVCS events.
- In general, results are compatible with the published RG-A results.

## Outlook

- □ An analysis note will be submitted to review soon.
- □ An analysis on pass2 data is planned as well.
- □ The next step is to test this method on RG-B data for nDVCS BSA measurements.





# Thanks



# Backup

## Phase space with proton information - Inbending

#### Let's compare the $(Q^2, x_B)$ phase space.



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## Phase space without proton information -Inbending

#### Let's compare the $(Q^2, x_B)$ phase space.



## Kinematics with proton information



**Figure:** Momentum of the final particles as a function of the polar angle (first row) and detection polar vs azimuthal angle for each final state.

## Kinematics without proton information



**Figure:** Momentum of the final particles as a function of the polar angle (first row) and detection polar vs azimuthal angle for each final state .

# $ep \rightarrow e\gamma p$ : Model training - Outbending torus

The main contamination channel is  $ep \rightarrow ep\pi^0 \rightarrow ep\gamma(\gamma)$ .



## $ep \rightarrow e\gamma p$ : BDT - Outbending torus

We extract a dataset with DVCS $\sim$  96.6% and DVMP $\sim$  3.4%.



# $ep \rightarrow e\gamma(p)$ : NP BDT - Inbending

To optimize the DVCS event selection, a Boosted Decision Tree (BDT) is trained to classify the events.

- □ Discriminating variables:  $\{M_{e\gamma X}^2, M_{eX}^2, t\}$ .
- □ Simulated DVCS as signal.
- $\square$   $\pi^0$  production data, reconstructed as DVCS, as background.



(a) BDT output distributions for different datasets.

(b) ROC curve of the model and applied cut.

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# $ep \rightarrow e\gamma(p)$ : Model training NP- Outbending



**Figure:** Missing masses  $M_{e\gamma X}^2$ ,  $M_{eX}^2$  and *t*, normalized to 1, for data (red), training DVCS dataset (black) and training  $\pi^0$  dataset (blue).

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# eppi0 NP outbending



## **RGA** bins

Bin no.	$Q^2$ (GeV <sup>2</sup> )	x <sub>B</sub>	t'  (GeV <sup>2</sup> )	Bin no.	$Q^2$ (GeV <sup>2</sup> )	$x_B$	t'  (GeV <sup>2</sup> )	Bin no.	$Q^2(\text{GeV}^2)$	x <sub>B</sub>	t'  (GeV <sup>2</sup> )
1		< 0.13		25		< 0.16		49	3.25 - 5.0	< 0.33	< 0.2
2	< 1.4	0.13 - 0.21	< 0.2	26	1.8 - 2.4	0.16 - 0.26	< 0.2	50		> 0.33	
3		> 0.21		27		> 0.26		51		< 0.33	0.2 - 0.4
4		< 0.13		28		< 0.16		52		> 0.33	
5		0.13 - 0.21	0.2 - 0.4	29		0.16 - 0.26	0.2 - 0.4	53		< 0.33	0.4 - 0.8
6		> 0.21		30		> 0.26		54		> 0.33	
7		< 0.13		31		< 0.16		55		< 0.33	> 0.8
8		0.13 - 0.21	0.4 - 0.8	32		0.16 - 0.26	0.4 - 0.8	56		> 0.33	
9		> 0.21		33		> 0.26		57	> 5.0	< 0.55	< 0.2
10		< 0.13		34		< 0.16		58		> 0.55	
11		0.13 - 0.21	> 0.8	35		0.16 - 0.26	> 0.8	59		< 0.55	0.2 - 0.4
12		> 0.21		36		> 0.26		60		> 0.55	
13		< 0.13		37		< 0.21		61		< 0.55	0.4 - 0.8
14	1.4 - 1.8	0.13 - 0.21	< 0.2	38	2.4 - 3.25	0.21 - 0.33	< 0.2	62		> 0.55	
15		> 0.21		39		> 0.33		63		< 0.55	> 0.8
16		< 0.13		40		< 0.21		64		> 0.55	
17		0.13 - 0.21	0.2 - 0.4	41		0.21 - 0.33	0.2 - 0.4				
18		> 0.21		42		> 0.33					
19		< 0.13		43		< 0.21					
20		0.13 - 0.21	0.4 - 0.8	44		0.21 - 0.33	0.4 - 0.8				
21		> 0.21		45		> 0.33					
22		< 0.13		46		< 0.21					
23		0.13 - 0.21	> 0.8	47		0.21 - 0.33	> 0.8				
24		> 0.21		48		> 0.33					

## $ep \rightarrow e\gamma(p)$ : BSA - Benchmark measurements

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# **Bin 16 - Inbending:** $1.4 < Q^2 (\text{GeV}^2) < 1.8$ , $x_B < 0.13$ , $0.2 < -t (\text{GeV}^2) < 0.4$



## $ep \rightarrow e\gamma(p)$ : BSA - Benchmark measurements

**Bin 26 - Inbending:**  $1.8 < Q^2 (\text{GeV}^2) < 2.4, \ 0.16 < x_B < 0.26, -t(\text{GeV}^2) < 0.2$ 

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## $ep \rightarrow e\gamma(p)$ : BSA - Benchmark measurements

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**Bin 28 - Inbending:**  $1.8 < Q^2 (\text{GeV}^2) < 2.4$ ,  $x_B < 0.16$ ,  $0.2 < -t (\text{GeV}^2) < 0.4$ 



# The update: Now with the correct *t* definition!



## k'>1 GeV?



**Figure:** Sampling fraction vs electron momentum with proton detection on the inbending torus configuration.

#### SF is 0.23 in all momentum ranges.

## k'>1 GeV?



Figure: BSA at bin 16.

It may affect importantly the BSA.

## BDT score per bin

About the performance...

- BDT classification without proton information keeps 80% of the events classified with proton information
- $\hfill\square$  That represents 30% (40%) of the in(out)bending datasets.



## $\eta$ contamination



Figure: 2-photon invariant mass.

 $\eta$  contamination is at least 10 times smaller than  $\pi^0$ .

## $\eta$ contamination



**Figure:**  $\pi^0$  and  $\eta$  contamination (%) per bin after BDT for the inbending dataset without proton information.

- If proton information is included: contamination is less than 1% on all bins.
- □ If proton information is ignored: contamination is less than 2% on most bins. Maximum is 7%.

## $\eta$ contamination



Figure: 2-photon invariant mass.

- If proton information is included: contamination is less than 1% on all bins.
- □ If proton information is ignored: contamination is less than 2% on most bins. Maximum is 7%.
  - However, more than half the events are from combinatorial background.
  - □ No subtraction was implemented then.

## Fixed BSA cross-check

Using dvcsgen, a DVCS and  $\pi^0$  asymmetry was generated.

 $\square$  1000 jobs with 10k events on each one for DVCS and  $\pi^0$ .

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 $\hfill\square$  –scale 2 , for getting a custom BSA



Figure: Generated BSA at bin 26

#### Goal is to recover unit BSA amplitude.

# Fixed BSA cross-check

#### BSA on the combined dataset.



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#### BDT removes a big part of the contamination.

## Fixed BSA cross-check



After BDT and background subtraction we recover the full amplitude.

## Fixed BSA cross-check: No proton

#### Now ignoring the proton information:



Figure: Generated BSA at bin 26

Goal is to recover unit BSA amplitude.

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## Fixed BSA cross-check: No proton

#### BSA on the combined dataset.



#### BDT removes a big part of the contamination.

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## Fixed BSA cross-check: No proton



# After BDT and background subtraction we recover the full amplitude.

## **RC** factor



# **Computing systematics**

$$\begin{array}{ll} \text{Merging BSA} \quad A = \frac{\frac{A_{inb}}{\sigma(A_{inb})} + \frac{A_{outb}}{\sigma(A_{outb})}}{\sqrt{\frac{1}{\sigma(A_{inb})^2} + \frac{1}{\sigma(A_{outb})^2}}} \\ \text{Merging kin} \quad Q^2 = \frac{Q_{inb}^2 n_{inb} + Q_{outb}^2 n_{outb}}{n_{inb} + n_{outb}} \\ \text{Merging sys} \quad A_{\pm} = \frac{\frac{A_{inb} \pm \sigma_{outb}^{cut}}{\sigma(A_{inb})} + \frac{A_{outb} \pm \sigma_{outb}^{cut}}{\sigma(A_{outb})^2}}{\sqrt{\frac{1}{\sigma(A_{inb})^2} + \frac{1}{\sigma(A_{outb})^2}}} \\ \\ \text{Bkg sub} \\ \text{sys err} \quad \sigma^{bkg} = \frac{A^{raw} - A^{\pi^0}}{(1 - f)^2} \delta f \end{array}$$

$$\sigma(A) = \frac{1}{\sqrt{\frac{1}{\sigma(A_{inb})^2} + \frac{1}{\sigma(A_{outb})^2}}}$$
$$\sigma(Q^2) = \frac{\sigma(Q^2_{inb})n_{inb} + \sigma(Q^2_{outb})n_{outb}}{n_{inb} + n_{outb}}$$
$$\sigma^{cut} = \sqrt{\frac{(A_+ - A_0)^2 + (A_- - A_0)^2}{2}}$$