Reconstructing parton collisions with machine learning techniques

G. Sborlini[1,2], D. Rentería-Estrada[3], R. Hernández-Pinto[3], P. Zurita[4]

[1]Departamento de Fisica Fundamental and IUFFyM, Universidad de Salamanca, Salamanca, Spain.
[2]Deutsches Elektronen-Synchrotron DESY, Zeuthen, Germany.
[3]FCFM, Universidad Autónoma de Sinaloa, México.
[4]Institut für Theoretische Physik, Regensburg, Germany.

VNiVERSiDAD Đ SALAMANCA
CAMPUS DE EXCELENCIA INTERNACIONAL

ICHEP 2022 XLI International Conference on High Energy Physics Bologna (Italy) 6 13 07 2022

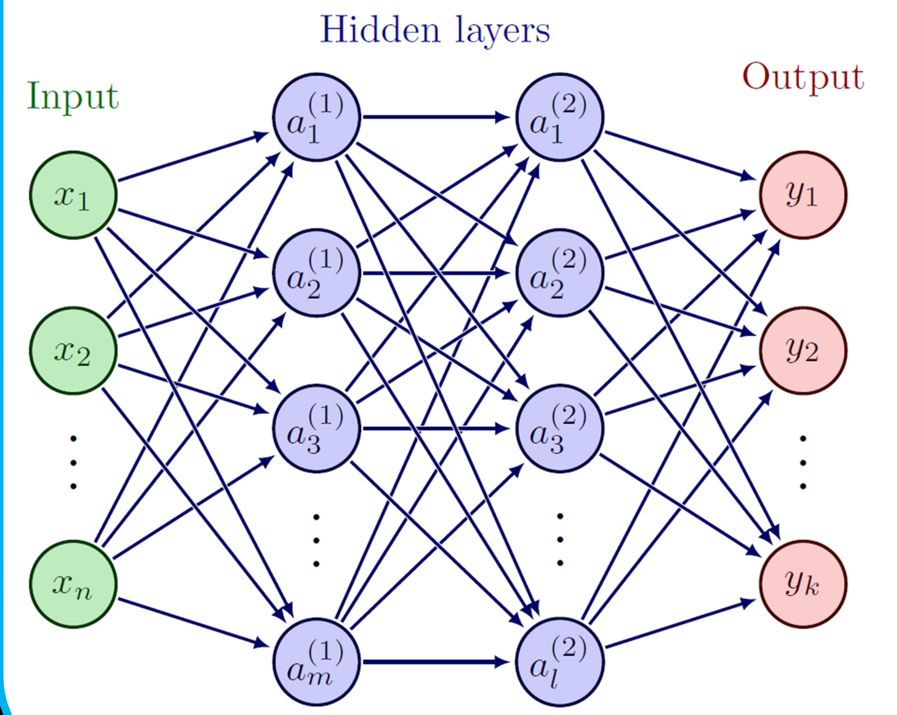
Abstract.

Having access to the parton-level kinematics provides new tools to understand the internal structure of hadrons. In this work, we explore the application of Machine-Learning (ML) techniques to model the partonic momentum fractions in terms of experimentally-accessible variables.

In first place, we calculated the differential hadronic cross-section including up to Next-to-Leading Order QCD and Leading-Order QED corrections. Using a code based on Monte-Carlo integration, we simulate the collisions and analyze the events to determine the correlations among measurable and partonic quantities. Then, we apply ML algorithms that allow us to find the momentum fractions of the partons involved in the process in terms of suitable combinations of the final state momenta.

Motivation and introduction.

- We tested our proof-of-concept with the photon-hadron production at colliders, since the photon provides a clean probe to access the parton kinematics.
- The aim is reconstruct the momentum fraction $\mathbf{x_1}$, $\mathbf{x_2}$ and $\mathbf{z}$ of the original partons in the interaction, taking into account up to NLO QCD + LO QED effects.

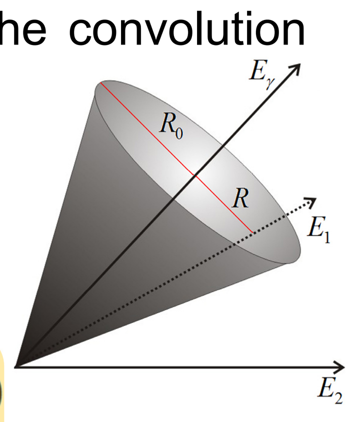


- Parton kinematics is not physically-defined (*it is a model*). Thus, we try to provide a quantitative estimation of their *most probable values*.
- For this purpose, we trained Neuronal Networks (NN) to predict the Monte-Carlo partonic momentum fractions in terms of external momenta.
- A Multilayer Perceptron (MLP) with 5 hidden layers, 300 neurons per layer and a ReLu (Unitary Linear Rectifier) activation function was implemented.

Computational setup.

- In hadron-hadron collisions, the cross-section is described by the convolution between PDFs, FFs and the partonic cross-section:

$$d\sigma_{H_1H_2\to h\gamma} = \sum_{a_1a_2a_3}\int dx_1\,dx_2\,dz\, f_{H_1/a_1}(x_1,\mu_I)\, f_{H_2/a_2}(x_2,\mu_I)\, D_{a_3/h}(z,\mu_F) \times d\hat{\sigma}_{a_1 a_2\to a_3\gamma}(x_1P_1, x_2P_2, P^h/z, P^\gamma;\mu_I,\mu_F,\mu_R)$$
$$+ \sum_{a_1a_2a_3}\sum_{a_4\in \mathrm{QCD}}\int dx_1\,dx_2\,dz_1\,dz_2\, f_{H_1/a_1}(x_1,\mu_I)\, f_{H_2/a_2}(x_2,\mu_I)\, D_{a_3/h}(z_1,\mu_F) \times \tilde{D}_{a_4/\gamma}(z_2,\mu_F)\, d\hat{\sigma}_{a_1a_2\to a_3a_4}(x_1P_1, x_2P_2, P^h/z_1, P^\gamma/z_2;\mu_I,\mu_F,\mu_R)$$



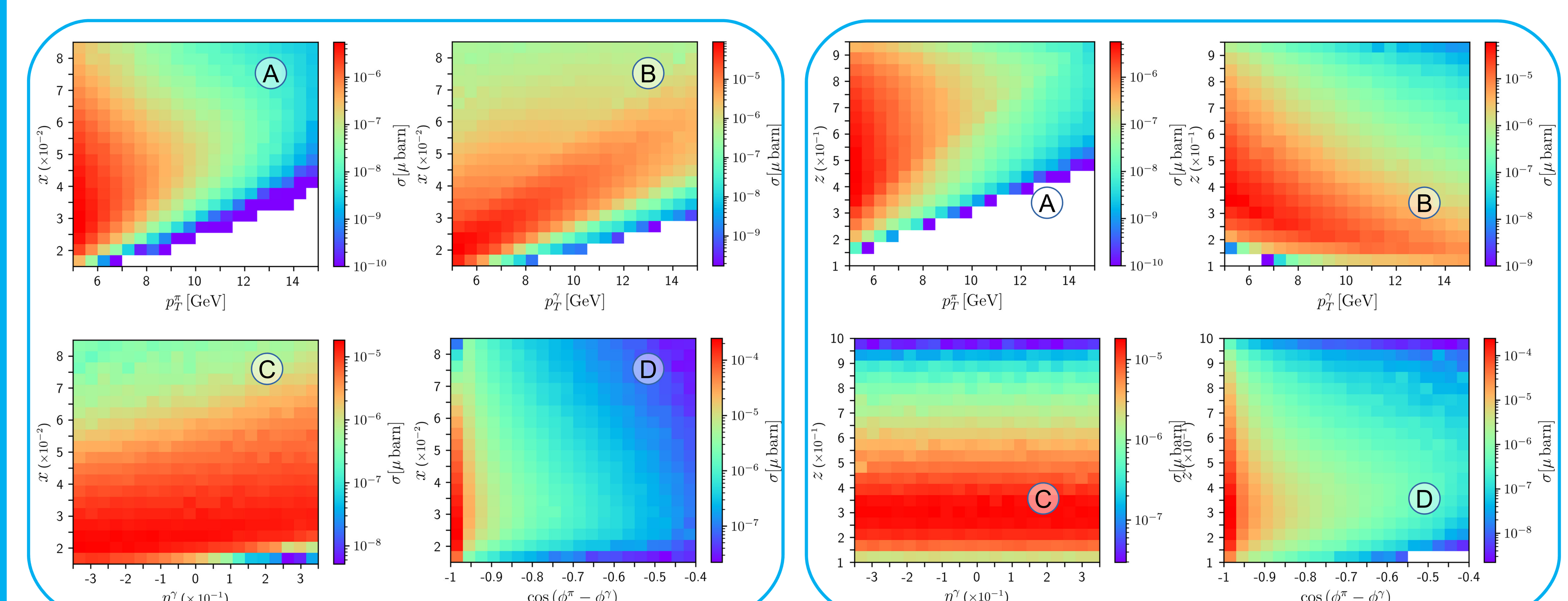
Smooth cone isolation prescription

- **Binning strategy @ NLO:** different contributions live in different phase-spaces. Thus, real (2-to-3), virtual (2-to-2) and counter-terms (2-to-2) terms are combined by defining bins in the measurable variables and integrating the fully differential cross-section (computed through FKS method):

$$\bar{\mathcal{V}}_{\mathrm{Exp}} = \{\bar{p}_T^\gamma, \bar{p}_T^\pi, \bar{\eta}^\gamma, \bar{\eta}^\pi, \overline{\cos}(\phi^\pi-\phi^\gamma)\} \quad \sigma_j(\bar{p}_T^\gamma, \bar{p}_T^\pi, \bar{\eta}^\gamma, \bar{\eta}^\pi, \overline{\cos}(\phi^\pi-\phi^\gamma)) = \int_{(p_T^\gamma)_{j,\mathrm{MIN}}}^{(p_T^\gamma)_{j,\mathrm{MAX}}} dp_T^\gamma \int_{(p_T^\pi)_{j,\mathrm{MIN}}}^{(p_T^\pi)_{j,\mathrm{MAX}}} dp_T^\pi \ldots \times \int dx_1 dx_2 dz\, d\hat{\sigma}$$

Discretized space of measurable variables → Binned cross-section

Analysis of correlations.



We studied the correlations among the momentum fractions **x** *(left panel)* – **z** *(right panel)* and the experimentally accessible variables: **pion transverse momentum** *(A)*, **photon transverse momentum** *(B)*, **photon rapidity** *(C)* and the **relative azimuthal angle of the pion-photon pair** *(D)*. Each bin is colored according to the value of the integrated cross-section. It provides an idea about the variables with more influence on the determination of the partonic momentum fractions.

Parton kinematics reconstruction.

- At LO, $\mathbf{x_1}$, $\mathbf{x_2}$ and $\mathbf{z}$ are unambiguously fixed by external particle's kinematics:

$$X_{1,\mathrm{REC}} = \frac{p_T^\gamma \exp(\eta^\pi) + p_T^\gamma \exp(\eta^\gamma)}{\sqrt{S_{CM}}} \qquad X_{2,\mathrm{REC}} = \frac{p_T^\gamma \exp(-\eta^\pi) + p_T^\gamma \exp(-\eta^\gamma)}{\sqrt{S_{CM}}} \qquad Z_{\mathrm{REC}} = \frac{p_T^\pi}{p_T^\gamma}$$

- This is no longer true at NLO, since real radiation includes extra particles in the final state (and momentum conservation differs from LO kinematics). So, given a point in the grid, $p_j = \{\bar{p}_T^\gamma, \bar{p}_T^\pi, \bar{\eta}^\gamma, \bar{\eta}^\pi, \overline{\cos}(\phi^\pi-\phi^\gamma)\} \in \bar{\mathcal{V}}_{\mathrm{Exp}}$, we define *averages*:

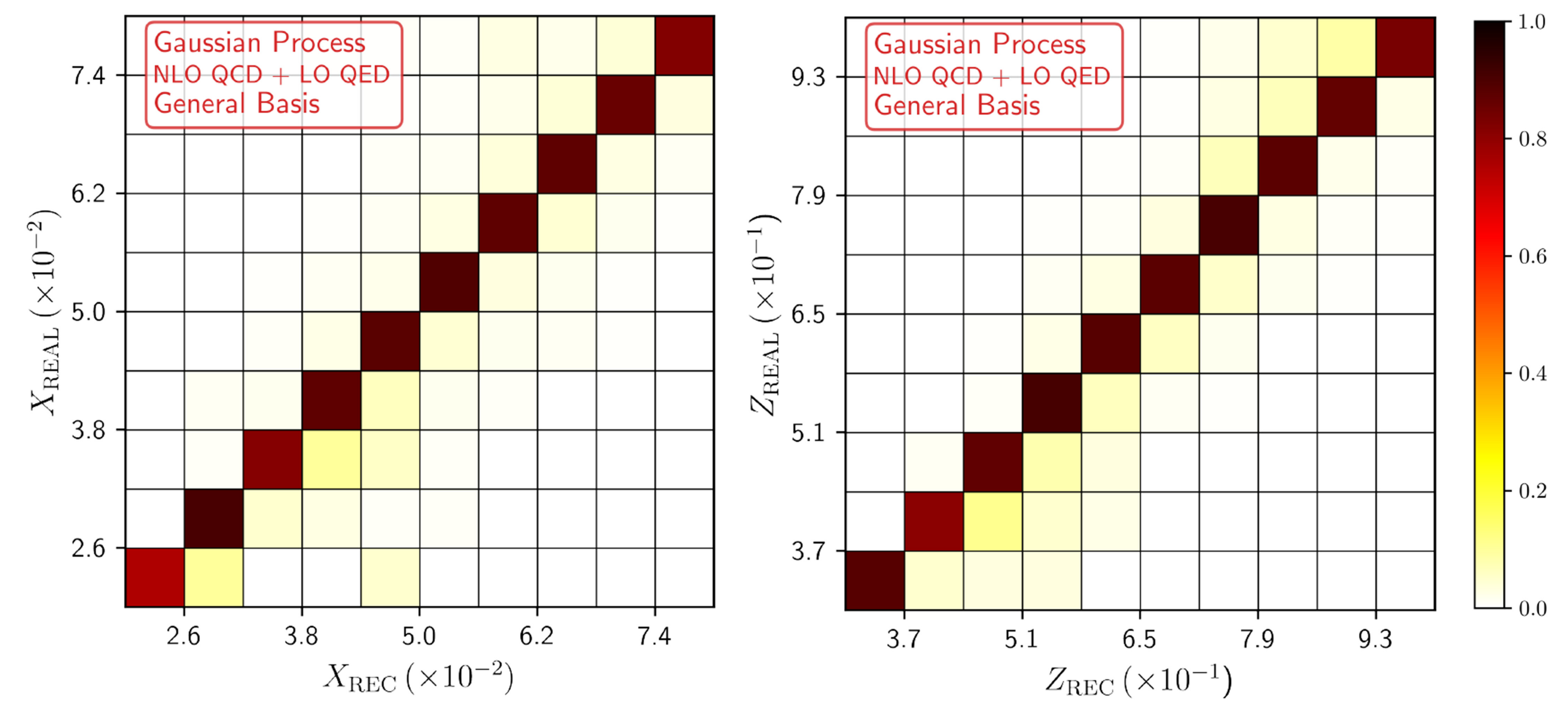
$$\langle x\rangle_j = \sum_i x_i \frac{d\sigma_j}{dx}(p_j; x_i) \qquad \langle z\rangle_j = \sum_i z_i \frac{d\sigma_j}{dz}(p_j; z_i)$$

- Then, we use ML to find mappings connecting the points in the grid with the average value of the momentum fraction per bin, *weighted by the cross-section*:

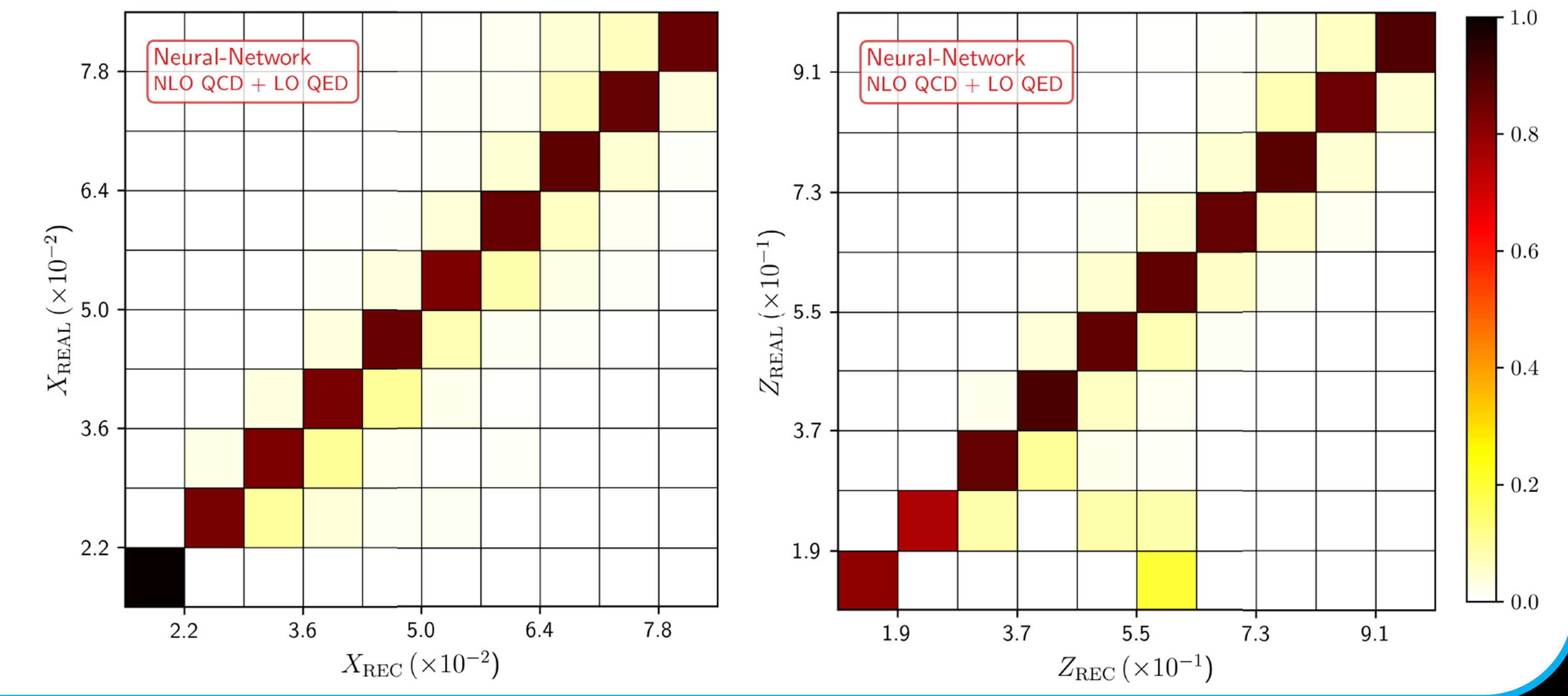
$$X_{\mathrm{REC}} := \bar{\mathcal{V}}_{\mathrm{Exp}} \longrightarrow \bar{X}_{REAL} = \{\langle x\rangle_j\} \qquad Z_{\mathrm{REC}} := \bar{\mathcal{V}}_{\mathrm{Exp}} \longrightarrow \bar{Z}_{REAL} = \{\langle z\rangle_j\}$$

- Linear Method, Gaussian Regression and Neural Networks were implemented. The last two provide the best reconstruction (with less constraints).

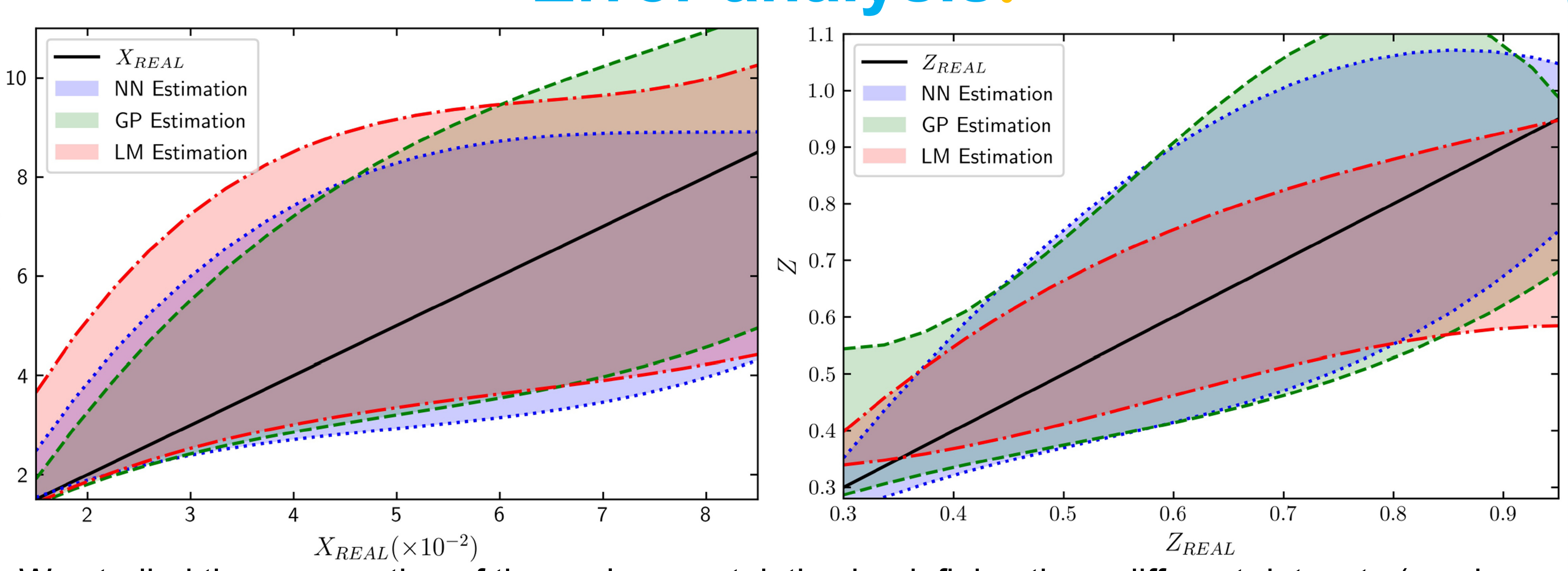
Gaussian Regression



Neural Networks



Error analysis.



We studied the propagation of the scale uncertainties by defining three different datasets (varying the renormalization and factorization scales by a factor 2, up and down). With these datasets, we trained three different estimators and evaluated them in each point of the grid:

$$X(p_j) \equiv \{X_{\mathrm{REC}}^{(\xi=2)}(p_j), X_{\mathrm{REC}}^{(\xi=1)}(p_j), X_{\mathrm{REC}}^{(\xi=1/2)}(p_j)\} \Longrightarrow X_{\mathrm{REC}}(p_j) = \overline{X(p_j)} \pm \frac{\max(X(p_j)) - \min(X(p_j))}{2}$$

The average error is 7.5% for **x** and 5.4% for **z**, running over the whole reconstruction range.

Conclusions.

- Parton level kinematics were reconstructed using ML techniques.
- The results are in agreement with previous findings, *but they require much less human intervention*. In particular, NN do not even need to select a function basis (GR and LM use basis motivated by the correlation studies).
- This PoC could be used to improve our knowledge of parton-level processes.

References

[1] D. F. Rentería-Estrada, R. J. Hernández-Pinto, G. F. R. Sborlini and P. Zurita, ***Reconstructing partonic kinematics at colliders with Machine Learning***, arXiv:2112.05043 [hep-ph].

[2] D. F. Rentería-Estrada, R. J. Hernández-Pinto and G. F. R. Sborlini, ***Analysis of the Internal Structure of Hadrons Using Direct Photon Production***, Symmetry 13 (2021) 6, 942. arXiv:2104.14663 [hep-ph].

[3] D. de Florian and G. F. R. Sborlini, ***Hadron plus photon production in polarized hadronic collisions at next-to-leading order accuracy***, Phys.Rev.D 83 (2011) 074022. arXiv:1011.0486 [hep-ph].