## Parton distribution functions and machine learning

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in collaboration with D. Rentería-Estrada, R. Hernández-Pinto and G. Sborlini

## Outlook

- Parton distributions functions:
- Some history.
- How to compute them.
- Technical details.
- Using machine learning to learn about PDFs:
- Motivation.
- Accessing momentum fractions in $p+p$ with ML (several methods and results).
- Going greener with ML (preliminary results).
- Summary


# "All" about parton distribution functions 



## 1960s: Deep(ly) Inelastic Scattering

$$
\begin{aligned}
& Q^{2}=-\left(k-k^{\prime}\right)^{2} \quad x=\frac{Q^{2}}{2 P \cdot q} \quad y=\frac{P \cdot q}{P \cdot k} \\
& \frac{d^{2} \sigma}{d x d Q^{2}} \propto F_{2}\left(x, Q^{2}\right)-\frac{y^{2}}{1+(1-y)^{2}} F_{L}\left(x, Q^{2}\right)
\end{aligned}
$$


$+6^{\circ} \quad-18^{\circ}$
$\times 10^{\circ} \Delta 26^{\circ}$


- The scaling is expected if DIS is the incoherent scattering of partons (Feynman, 1969).

$$
F_{2}^{L O}(x)=x \sum_{i=1}^{n_{f}} e_{i}^{2} f_{i / h}(x)
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$f_{i / h}(x)$ is the probability density of finding the parton $i$ inside the hadron $h$ with $\boldsymbol{x}$. These are called Parton Distribution Functions (PDFs).

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- Dokshitzer-Gribov-Lipatov-Altarelli-Parisi (DGLAP) equations give the evolution with the scale, while mixing the partons.

$$
\mu^{2} \frac{d}{d \mu^{2}} f_{a / h}(x, \mu)=\int_{x}^{1} \frac{d \xi}{\xi} \sum_{b} P_{a / b}\left(\frac{x}{\xi}, \alpha_{s}(\mu)\right) f_{b / h}(\xi, \mu)
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They are universal, so any process that is an inclusive hard scattering can be written as

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d \sigma^{D I S}=\sum_{i} d \sigma^{l+i \rightarrow l^{\prime}} \otimes f_{i} \quad d \sigma^{D Y}=\sum_{i, j} d \sigma^{i+j \rightarrow l+\bar{l}} \otimes f_{i} \otimes f_{j}
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## Without PDFs there is no prediction!

I will adhere the KISS principle and stick to collinear PDFs.

## How to compute PDFs

- PDFs have formal definitions in terms of operators, for example

$$
\begin{array}{cc}
f_{j / h}(x, \mu)=\frac{1}{4 \pi} \int d y^{-} e^{-i x P^{+} y^{-}}\left\langle P^{+}, \overrightarrow{0}_{T}\right| \bar{\psi}_{j}\left(0, y^{-}, \overrightarrow{0}_{T}\right) \gamma^{+} \mathcal{O} \psi_{j}\left(0,0, \overrightarrow{0}_{T}\right)\left|P^{+}, \overrightarrow{0}_{T}\right\rangle_{\bar{M} S} \\
\mathcal{O}=\mathscr{P} \exp \left(i g \int_{0}^{y^{-}} d z^{-} A_{a}^{+}\left(0, z^{-}, \overrightarrow{0}_{T}\right) t_{a}\right) & P^{ \pm}=\left(P^{0} \pm P^{3}\right) / \sqrt{2}
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So we can't compute these from first principles in PQCD, we must resort to phenomenology. We do global fits.

## Steps for a "traditional" fit:

Choose:

- a factorisation scheme
- an order in perturbation theory*
- a starting scale $Q_{0}$ (so that above it pQCD is valid)
- the data to be fitted
- a heavy flavour scheme


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- a heavy flavour scheme
- Parametrise the quark and gluon distribution (or a combination of them):

$$
x f_{i}\left(x, Q_{0}^{2}\right)=A_{i} x^{\alpha_{i}}(1-x)^{\beta_{i}} P\left(x, c_{i}\right)
$$

- Solve the DGLAP equations for the measured kinematics.
- Compute the hard cross sections for the observables.
- Convolute PDFs and partonic cross-sections.
- Compute this quantity and minimise it:

$$
\sum_{i, j=1}^{N_{\text {data }}}\left[\sigma_{\text {exp }}-\sigma_{t h}\right]_{i} C_{i j}^{-1}\left[\sigma_{\text {exp }}-\sigma_{t h}\right]_{j}=\chi_{\text {test }}^{2}
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- Compute this quantity and minimise it:

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\sum_{i, j=1}^{N_{\text {data }}}\left[\sigma_{\text {exp }}-\sigma_{t h}\right]_{i} C_{i j}^{-1}\left[\sigma_{e x p}-\sigma_{t h}\right]_{j}=\chi_{t e s t}^{2}
$$

By the CLT, each term in the sum is distributed according to the square of a standard Gaussian.
If we use $d$ parameters, $\chi_{\text {test }}^{2}$ follows a $\chi^{2}$ distribution with $N_{\text {data }}-d$ degrees of freedom.

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E\left[\chi_{\text {test }}^{2}\right]=N_{\text {data }}-d=N_{\text {d.o.f. }} \Longrightarrow E\left[\chi_{\text {test }}^{2}\right] / N_{\text {d.o.f. }}=1
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- When we reach this point (the fit is "good enough") we can be happy and store the final parameters.
- Use some method to estimate theoretical error bands.
- Create grids in $x$ and $Q^{2}$, and provide an interpolator for the grid. Make it publicly available (LHAPDF).


## Some details

- The basic process is DIS with photon/Z boson exchange:

$$
\begin{aligned}
& \frac{d^{2} \sigma}{d x d Q^{2}} \propto F_{2}\left(x, Q^{2}\right)-\frac{y^{2}}{1+(1-y)^{2}} F_{L}\left(x, Q^{2}\right) \\
& F_{2}\left(x, Q^{2}\right)=\sum_{i=0}^{+\infty} \alpha_{s}^{i}\left(Q^{2}\right)\left[C_{2, q}^{i, N S} \otimes f_{q}^{N S}+C_{2, q}^{i S} \otimes f_{q}^{S}+C_{2, g}^{i} \otimes f_{g}\right] \\
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& f_{q}^{N S}\left(x, Q^{2}\right)=\sum_{i=1}^{n_{f}} e_{i}^{2} f_{i}\left(x, Q^{2}\right) \\
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We need to use other observables, such as Charged Current DIS to distinguish flavours.
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We can use "neutrons", but it is still to enough, due to the kinematic reach of the data...

We use p+p!


- Let us see for example Drell-Yan: $\quad \frac{d^{2} \sigma}{d x_{F} d Q^{2}}=\frac{d^{2} \sigma^{A}}{d x_{F} d Q^{2}}+\frac{d^{2} \sigma^{C}}{d x_{F} d Q^{2}}$

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\frac{d^{2} \sigma^{A}}{d x_{F} d Q^{2}}=\frac{4 \pi \alpha^{2}}{9 Q^{2} s} \sum_{i} e_{i}^{2} \int_{x_{1}}^{1} d t_{1} \int_{x_{2}}^{1} d t_{2} \frac{d^{2} \hat{\sigma}^{A}}{d x_{F} d Q^{2}}\left[f_{i}\left(t_{1}, Q^{2}\right) \bar{f}_{i}\left(t_{2}, Q^{2}\right)+\bar{f}_{i}\left(t_{1}, Q^{2}\right) f_{i}\left(t_{2}, Q^{2}\right)\right]
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- More importantly, beyond LO the $x_{1}, x_{2}$ are not the momentum fractions of the partons in the hard interaction!

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x_{1}, x_{2}=\sqrt{\frac{M^{2}}{s}} e^{ \pm y}
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## Machine learning for PDFs

## Motivation

Not being able to access the real $x_{1}, x_{2}$ from measuring the kinematics is not exclusive of the Drell-Yan process. It happens for all p+p collisions.

- And can have significant impact: e.g. in $\mathrm{p}+\mathrm{Pb}$ collisions $\quad x_{1}, x_{2}=\sqrt{\frac{M^{2}}{s}} e^{ \pm y}$


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- We want to use ML to find a link between the measurable quantities and the parton momentum fractions.


## Accessing the kinematics using ML

- We looked at one particular process: $\quad p+p \rightarrow \pi^{+}+\gamma$
- Reconstructed $x_{1}, x_{2}$ and $z$ from momenta of $\pi^{+}, \gamma$
- For RHIC kinematics, so we could compare with previous results.
D. de Florian and G. Sborlini,

Phys.Rev.D 83 (2011) 074022

## First: check the dependences on the kinematics

- Transverse momentum dependence:


- $x_{1}=x, z$ dependences:




## Second: check correlations

LO Kinematics $\quad x_{1,2}=\frac{p_{T}^{\gamma}}{\sqrt{s}}\left(e^{\eta^{ \pm \pi}}+e^{\eta^{ \pm \gamma}}\right) \quad z=\frac{p_{T}^{\pi}}{p_{T}^{\gamma}}$

- $\quad x$ vs. $p_{T}$


- $\quad z$ vs. $p_{T}$




## Second: check correlations

NLO Kinematics $\quad x_{1,2}=? \quad z=?$





## Kinematics: LO <br> $$
x_{1,2}^{r e c .}=\frac{p_{T}^{\gamma}}{\sqrt{s}}\left(e^{ \pm \eta^{\pi}}+e^{ \pm \eta^{\gamma}}\right)
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Experimental collaborations used

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x_{1,2}^{r e c .}=\frac{p_{T}^{\gamma} e^{ \pm \eta^{\pi}}-\cos \left(\phi^{\pi}-\phi^{\gamma}\right) p_{T}^{\gamma} e^{ \pm \eta^{\gamma}}}{\sqrt{s}}
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D. de Florian, R. Sassot, M. Epele, R.J. Hernández-Pinto and M. Stratmann, PRD 91, 014035.

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The code now includes QED corrections:
D. Rentería-Estrada, R. Hernández-Pinto, G. Sborlini, Symmetry 13 (2021) 6, 942

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New numerical methods/tools available with tutorials "for dummies".

We're the dummies: we want to apply machine learning techniques to access the real momentum fractions and lower the assumptions.

At NLO we have real $(2 \rightarrow 3)$ and virtual $(2 \rightarrow 2)$ contributions and counterterms ( $2 \rightarrow 2$ ).

Cancellations can only happen in the MC integration when histograming.

$$
\begin{aligned}
& \left\{\bar{p}_{T}^{\gamma}, \bar{p}_{T}^{\pi}, \bar{\eta}^{\gamma}, \bar{\eta}^{\pi}, \overline{\cos }\left(\phi^{\pi}-\phi^{\gamma}\right)\right\} \in \overline{\mathscr{V}}_{\text {EXP }} \\
& \quad \sigma_{j}\left(\bar{p}_{T}^{\gamma}, \bar{p}_{T}^{\pi}, \bar{\eta}^{\gamma}, \bar{\eta}^{\pi}, \overline{\cos }\left(\phi^{\pi}-\phi^{\gamma}\right)\right)=\int_{\left(p_{T}^{\gamma}\right) ; M N}^{\left(p_{T}^{\gamma}\right)_{j, M A X}} d p_{T}^{\gamma} \int_{\left(p_{T}^{\gamma}\right)_{, M N N}}^{\left(p_{T}^{\pi}\right)_{, M A X}} d p_{T}^{\pi} \int d x_{1} d x_{2} d z d \bar{\sigma}
\end{aligned}
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At NLO we have real $(2 \rightarrow 3)$ and virtual $(2 \rightarrow 2)$ contributions and counterterms ( $2 \rightarrow 2$ ).

Cancellations can only happen in the MC integration when histograming.

$$
\begin{aligned}
& \left\{\bar{p}_{T}^{\gamma}, \bar{p}_{T}^{\pi}, \bar{\eta}^{\gamma}, \bar{\eta}^{\pi}, \overline{\cos }\left(\phi^{\pi}-\phi^{\gamma}\right)\right\} \in \overline{\mathscr{V}}_{E X P} \\
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\end{aligned}
$$

We weight the momentum fractions from the MC with the per-bin crosssection

$$
\left(x_{1}\right)_{j}=\sum_{i}\left(x_{1}\right)_{i} \frac{d \sigma_{j}}{d x_{1}}\left(p_{j} ;\left(x_{1}\right)_{i}\right) \quad(z)_{j}=\sum_{i}(z)_{i} \frac{d \sigma_{j}}{d z}\left(p_{j} ;(z)_{i}\right)
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$$

With this we search for the mapping

$$
X_{1, R E C}: \overline{\mathscr{V}}_{\text {EXP }} \rightarrow \bar{X}_{1, R E A L}=\left\{\left(x_{1}\right)_{j}\right\}
$$

- In general, in ML
training set, each entry is a d-dimensional vector ( $d=$ number of features)

target function, we estimate it using an algorithm that minimises a cost function
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## Linear regression

$$
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## Linear regression

 $\hat{y}=\theta_{0}+\theta_{1} x^{(1)}$"cheat": linear means linear in the parameters.

$$
\left[x^{(1)}\right]^{2}=x^{(2)} \longrightarrow \hat{y}=\theta_{0}+\theta_{1} x^{(1)}+\theta_{2} x^{(2)}
$$

the parameters minimise

$$
\min _{\theta}\|\hat{y}-y\|_{2}^{2}
$$

- Let us start with LO and use linear regression:
- Basis: $\mathscr{B}_{L O}=\left\{\frac{p_{T}^{\gamma} e^{\eta^{\pi}}}{\sqrt{s}}, \frac{p_{T}^{\gamma} e^{\eta^{\gamma}}}{\sqrt{s}}, \frac{p_{T}^{\gamma} e^{-\eta^{\pi}}}{\sqrt{s}}, \frac{p_{T}^{\gamma} e^{-\eta^{\gamma}}}{\sqrt{s}}, \frac{p_{T}^{\pi}}{p_{T}^{\gamma}}\right\}$

$$
x_{1,2}^{r e c .}=\frac{p_{T}^{\gamma}}{\sqrt{s}}\left(e^{\eta^{ \pm \pi}}+e^{\eta^{ \pm \gamma}}\right)
$$

$$
z^{r e c .}=\frac{p_{T}^{\pi}}{p_{T}^{\gamma}}
$$




## Linear regression

- We used three bases: "LO inspired", "general", "physically motivated"

$$
x_{1}^{L O}=\frac{p_{T}^{\gamma} e^{\eta^{\pi}}+p_{T}^{\gamma} e^{\eta^{\gamma}}}{\sqrt{s}}
$$

$$
\begin{aligned}
x_{1}^{p r o p .} & =\frac{p_{T}^{\gamma} \eta^{\eta^{\pi}}-\cos \left(\phi^{\pi}-\phi^{\gamma}\right) p_{T}^{\gamma} e^{\eta^{\gamma}}}{\sqrt{s}} \\
\mathscr{B}_{L O} & =\left\{\frac{p_{T}^{\gamma} e^{\eta^{\pi}}}{\sqrt{s}}, \frac{p_{T}^{\gamma} e^{\eta^{\gamma}}}{\sqrt{s}}, \frac{p_{T}^{\gamma} e^{-\eta^{\pi}}}{\sqrt{s}}, \frac{p_{T}^{\gamma} e^{-\eta^{\gamma}}}{\sqrt{s}}, \frac{p_{T}^{\pi}}{p_{T}^{\gamma}}\right\}
\end{aligned}
$$



$$
\mathscr{B}_{\mathrm{NLO}}^{X_{1}}=\left\{\frac{p_{T}^{\gamma}}{\sqrt{S_{C M}}} \exp \left(\eta^{\gamma}\right), \frac{p_{T}^{\gamma}}{\sqrt{S_{C M}}} \exp \left(\eta^{\pi}\right), \frac{p_{T}^{\pi}}{\sqrt{S_{C M}}} \exp \left(\eta^{\gamma}\right), \frac{p_{T}^{\pi}}{\sqrt{S_{C M}}} \exp \left(\eta^{\pi}\right), \frac{p_{T}^{\gamma} \mathscr{K}_{5}}{\sqrt{S_{C M}}} \exp \left(\eta^{\gamma}\right), \frac{p_{T}^{\gamma} \mathscr{K}_{5}}{\sqrt{S_{C M}}} \exp \left(\eta^{\pi}\right), \frac{p_{T}^{\pi} \mathscr{K}_{5}}{\sqrt{S_{C M}}} \exp \left(\eta^{\gamma}\right), \frac{p_{T}^{\pi} \mathscr{K}_{5}}{\sqrt{S_{C M}}} \exp \left(\eta^{\pi}\right)\right\}
$$

$$
\mathscr{K}_{5}=\cos \left(\phi^{\pi}-\phi^{\gamma}\right)
$$

## Linear regression

- We used three bases: "LO inspired", "general", "physically motivated"

$$
\mathscr{K}=\left\{\frac{p_{T}^{\gamma}}{\sqrt{s}}, \frac{p_{T}^{\pi}}{\sqrt{s}}, e^{\eta^{\gamma}}, e^{\eta^{\pi}}, \cos \left(\phi^{\pi}-\phi^{\gamma}\right)\right\}
$$

$$
X_{\text {REC }}=\sum_{i=1, i \neq 5}^{9}\left(a_{i}+b_{i} \mathscr{K}_{5}\right) \mathscr{K}_{i}+\sum_{i \leq j, i, i, j \neq 5, j, j \neq 5}\left(c_{i j}+d_{i j} \mathscr{K}_{5}\right) \mathscr{K}_{i} \mathscr{K}_{j}
$$

- 81 parameters in total.



## Linear regression

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$$
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- Remove contributions w.r.t. which we see no dependence ( $\sim 40$ parameters).



## Linear regression

## - For z:



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## The Radial Basis Function

$\mathbf{X}=\left(1, x_{1}, x_{2}\right)^{T}$

$$
\tilde{\mathbf{x}}=\left(1, x_{1}, x_{2}, x_{1}^{2}, x_{1} x_{2}, x_{2}^{2}\right)^{T}
$$

- How to pick $\tilde{\mathbf{X}}$ ? Before we did it by intuition.
- We replace $x^{(i)}$ by $f_{i}(x)=e^{-\frac{\left\|x-x^{(i)}\right\|_{2}^{2}}{2 / 2}}$

This Radial Basis Function
requires less elements (one per feature in the basis).
effectively considers infinite terms.

- is a popular form of the kernel method.



Similar results for the reconstruction of $z$.


## Neural networks: the basics



- Pass from one layer to the next by applying a non-linear activation function to a weighted sum of the previous layers.
- Pros: no need to play with the basis, less human bias (but not zero!)
- Cons: the complexity of the architecture requires more time for training.
- Also, one needs to choose the architecture.


## Neural networks



- For LO the complexity of the NN greatly surpasses the complexity of the problem.


## Going greener with ML

All the running of MC codes takes a long time to reach good precision.

Apart from boring, they carry a significant environmental impact (and to our pockets given the cost of electricity).

What can we do to make things faster using current available resources?

- Improve the codes: has to be done code by code.


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What can we do to make things faster using current available resources?

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Perhaps.

Most codes require non perturbative inputs (e.g. PDFs).

PDFs are provided as grids and functions that read the grids and interpolate over them (e.g. LHAPDF).

And this is quite efficient, as long as we don't need to run millions and millions of calculations.

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- A quick exploration shows that the time spent on the interpolation could be reduced $40-50 \%$ if we had analytical expressions for the PDFs.


## Goal: find an analytical $x$ and $Q^{2}$ form for a set of proton PDFs.

- We are working (for now) with HERAPDF2.0


## Idea and first results

- For most PDFs the x dependence at some initial scale is written as

$$
f_{i}\left(x, Q_{0}^{2}\right)=N_{i} x^{\alpha_{i}}(1-x)^{\beta_{i} i} P\left(x, c_{i j}\right)
$$

We propose

$$
f_{i}\left(x, Q_{0}^{2}, Q^{2}\right)=\left(N_{i}+g_{i, 1}\left(Q^{2}, Q_{0}^{2}\right)\right) x^{\alpha_{i}+g_{i i}\left(Q^{2}, Q_{0}^{2}\right)}(1-x)^{\beta_{i}+g_{i, 3}\left(Q^{2}, Q_{0}^{2}\right)} P\left(x, c_{i j}+g_{i, 4}\left(Q^{2}, Q_{0}^{2}\right)\right)
$$

with $g_{i, j}\left(Q_{0}^{2}, Q_{0}^{2}\right)=0$

In particular, for now, we're exploring $g_{i, 4}\left(Q^{2}, Q_{0}^{2}\right)=0$

With that simplification, the ratio of the same flavour PDF at different scales is

$$
R_{i}\left(x, Q_{0}^{2}, Q^{2}\right) \propto x^{g_{i, 2}\left(Q^{2}, Q_{0}^{2}\right)}(1-x)^{g_{i, 3}\left(Q^{2}, Q_{0}^{2}\right)}
$$

Taking logarithm

$$
\ln \left(R_{i}\right)=\ln \left(\frac{N_{i}^{\prime}\left(Q^{2}, Q_{0}^{2}\right)}{N_{i}}\right)+g_{i, 2}\left(Q^{2}, Q_{0}^{2}\right) \ln (x)+g_{i, 3}\left(Q^{2}, Q_{0}^{2}\right) \ln (1-x)
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$$

Now we only have to find the missing functions.

## First results: valence up



## First results: valence up




## First results: valence up






## The GAPP Initiative

This work is part of the GAPP Initiative.
We aim to quantify the carbon footprint of HEP research and study ways of reducing it.

If you are doing phenomenological studies and would like to contribute to the project, please send an email to gapp-initiative@googlegroups.com with:

- brief description of the simulation
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## Join the GAPP!

## Summary

- We have explored the applicability of ML techniques to better understand the underlying kinematics of a $p+p$ collision.
- The methodology can be used for any process by non-experts.
- The methods applied can result in a better reconstruction than in the original work, but physical intuition can play a relevant role.



- Higher sophistication of the method does not always translate into better results. E.g.:
exact relation known


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few minutes to train

several hours to train exploration of "good" architecture
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several hours to train exploration of "good" architecture
- Promising steps in speeding up the calculation of codes using PDFs.


# Thank you for your attention! 

