Machine Learning for the precision determination of Parton Distribution Functions

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Outline

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- Quantum Chromodynamics in a nutshell
 - The Standard Model
 - Parton Distribution Functions
 - Factorization theorem
- The N3PDF project
 - Motivation for PDFs determination.
 - Operator implementation in TensorFlow.
 - Results & Conclusions.

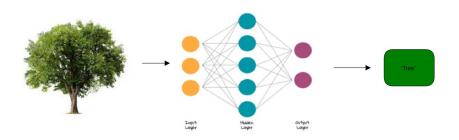
Machine Learning, an introduction

An example: Image recognition



Identify a particular object \longrightarrow hard problem for computers

Introducing neural networks



- Build a model that takes that array x and outputs y(x) such that for a tree outputs "tree"
- $y(x) = \sigma\{\mathbf{w} \cdot x + b\} \longrightarrow \text{Need for training } \mathbf{w}, b$

Training a neural network

• Multiply by a matrix of random weights and apply an activation function σ

$$y(x) = \sigma \left\{ \begin{pmatrix} w_{00} & \dots & w_{0n} \\ \vdots & \ddots & \vdots \\ w_{n0} & \dots & w_{nn} \end{pmatrix} \cdot \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} + \begin{pmatrix} b_1 \\ \vdots \\ b_n \end{pmatrix} \right\}$$

② First prediction will not be correct → Compute a loss function by comparing with truth

$$L = \sum_{i=1}^{N} (y(x) - y_i^{true})^2$$

Training a neural network

1 A perfect prediction will mean L = 0 Notice $L = L(w_{ij}, b_i)$

$$\nabla_{w} L = \frac{\partial L}{\partial w_{ij}}$$
$$\nabla_{b} L = \frac{\partial L}{\partial b_{i}}$$

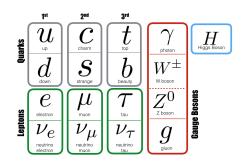
② Update w and b such that they minimize the loss function

$$w_{ij} \rightarrow w_{ij} + \alpha \nabla_w L$$

 $b_i \rightarrow b_i + \alpha \nabla_b L$

Quantum Chromodynamics in a nutshell

The Standard Model, a quick review



Quantum Field Theory describing physics at the TeV scale

- Fermions composing matter
- Bosons mediating interactions
- Scalar Higgs generating mass through SSB

Explore the strong interactions



How to explore proton's inner structure?

- Point-like projectile on the object → DIS
- ullet Smash the two objects \longrightarrow LHC physics

"A way to analyze high energy collisions is to consider any hadron as a composition of point-like constituents \longrightarrow partons" R.Feynman, 1969

Parton Distribution Functions





- Hadrons made of partonic objects non perturbative physics
- Interactions take place only at partonic level

Parton Distribution Functions: Probability distribution of finding a particular parton (u, d, ..., g) carrying a fraction x of the proton's momentum

Factorization theorem

Compute the cross section σ of a given process

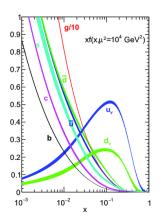


Factorize the problem into the partonic $\hat{\sigma}_{ij}$ and the PDFs at scale μ_F .

$$\sigma = \int_0^\infty dx_1 \ dx_2 \ f_{\alpha}(x_1, \mu_F) * f_{\beta}(x_2, \mu_F) * \hat{\sigma}_{ij}(\alpha_s(\mu_R), \mu_F) \ .$$

- Non perturbative physics hide inside the PDFs
- ullet Partonic $\hat{\sigma}_{ij}$ can be written as a series in perturbative expansion in $lpha_{s}$

What PDFs look like

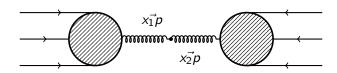


- Each parton has a different PDF $\longrightarrow u(x), d(x), ..., g(x)$.
- PDFs are not predicted, and can not be measured.
 - PDFs are extracted from data.

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Machine Learning for the precision determination of PDFs

What we actually measure



Convolute the partonic $\hat{\sigma}_{ii}$ with the PDFs \longrightarrow Observable σ .

$$\sigma = \int_0^\infty dx_1 \ dx_2 \ f_{\alpha}(x_1, \mu_F) * f_{\beta}(x_2, \mu_F) * \hat{\sigma}_{ij}(\alpha_s(\mu_R), \mu_F) \ .$$

In our language \longrightarrow vector of observables from a grid of x_i :

$$y_N = \sum_{i,j,\alpha,\beta} f_{\alpha}(x_i) f_{\beta}(x_j) F K_{Nij\alpha\beta}$$
.

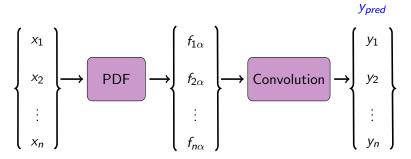
General structure of n3fit





- Use TensorFlow and Keras to determine PDFs
- See paper by S.Carraza J.Cruz-Martinez
 "Towards a new generation of parton densities with deep learning models", https://arxiv.org/abs/1907.05075

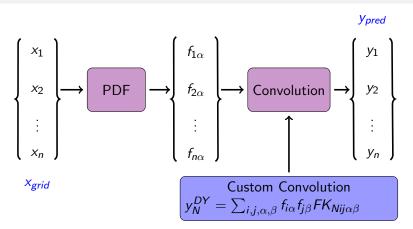
General structure



Xgrid

- **1** Build a NN to compute y_{pred} observables from a grid x_i
- ② Compute gradient $\nabla \chi^2$ by comparing with data
- \bigcirc Update values of PDF \longrightarrow Fit

Operator implementation



- lacktriangledown TF relies in symbolic computation \longrightarrow High memory usage
- 2 Implement c++ operator replacing the convolution

Results

Checking computation

DIS only:

	TensorFlow	Custom	Ratio
Convolution	1.9207904	1.9207904	1.0000000
	2.4611666	2.4611664	0.9999999
	1.3516952	1.3516952	1.0000000
Gradient	1.8794115	1.8794115	1.0000000
	1.505316	1.505316	1.0000000
	2.866085	2.866085	1.0000000

Results

Checking computation

Hadronic:

	TensorFlow	Custom	Ratio
Convolution	8.142365	8.142366	1.0000001
	8.947762	8.947762	1.0000000
	7.4513326	7.4513316	0.9999999
Gradient	18.525095	18.525095	1.0000000
	19.182995	19.182993	0.9999999
	19.551006	19.551004	0.9999999

Results

Memory saving

Hadronic only:

	TensorFlow	Custom Convolution	Diff
Virtual	17.7 GB	13.8 GB	3.9 GB
RES	12.1 GB	8.39 GB	3.2 GB

Global:

	TensorFlow	Custom Convolution	Diff
Virtual	23.5 GB	19.7 GB	3.8 GB
RES	18.4 GB	12.5 GB	5.9 GB

Summary & Conclusions

- PDFs are a crucial object in high energy physics.
- ML provides a new way of precisely determine PDFs.
- Operator implementation leads to saving memory taking full control on the computation.

Thank you!



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