Machine Learning for the precision determination of Parton Distribution Functions

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UNIVERSITÀ DEGLI STUDI DI MILANO

N3PDF
Machine Learning • PDFs • QCD

erc European Research Council

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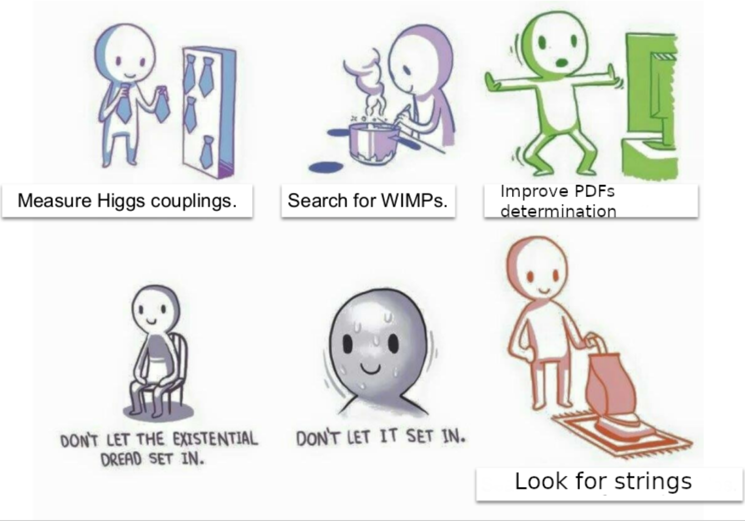
How to adult...


SHOP FOR A NEW TIE.
MAKE MACARONI
DO CARDIO.
DON'T LET THE EXISTENTIAL DREAD SET IN.
DON'T LET IT SET IN.
VACUUM THE RUG.

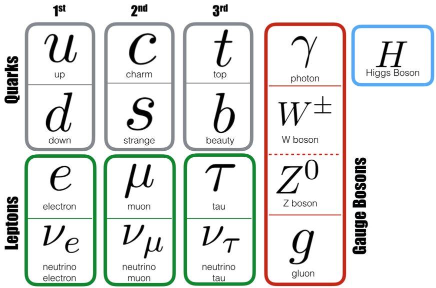
How to be a mature physicist...



Outline

1. Quantum Chromodynamics in a nutshell
   - The Standard Model
   - The strong interactions
   - Parton Distribution Functions
2. The N3PDF project
   - Machine Learning for PDFs determination
   - Operator implementation in TensorFlow
   - Results & Conclusions

Quantum Chromodynamics in a nutshell



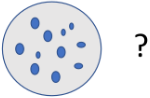
Quantum Field Theory describing physics at the TeV scale

1. Fermions composing matter
2. Bosons mediating interactions
3. Scalar Higgs generating mass

Quantum Chromodynamics

Explore the strong interactions

How to explore proton's inner structure?

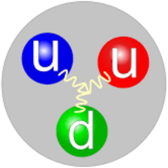


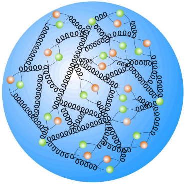
- Point-like projectile on the object $\longrightarrow$ DIS
- Smash the two objects $\longrightarrow$ LHC physics

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

Quantum Chromodynamics

Parton Distribution Functions



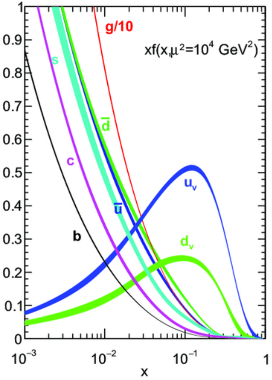


- Hadrons made of partonic objects $\longrightarrow$ non perturbative physics
- Interactions take place only at partonic level

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

Quantum Chromodynamics

What PDFs look like



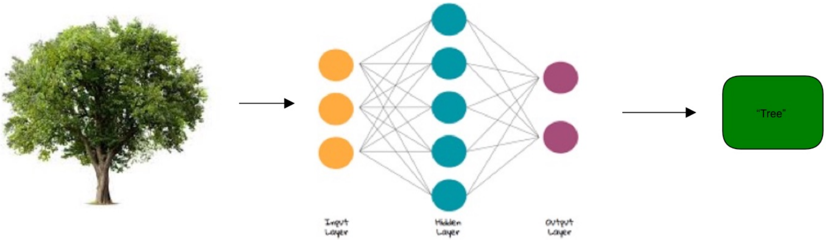
- Each parton has a different PDF $\longrightarrow$ $u(x)$, $d(x)$, ..., $g(x)$
- PDFs are not predicted, and can not be measured
- PDFs are extracted from data

The N3PDF project

Machine Learning for the precision determination of PDFs

The N3PDF project

Machine Learning

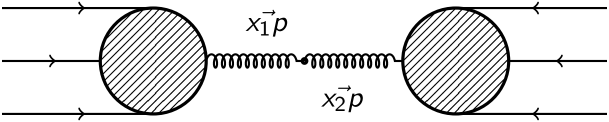


1. ML algorithms solve *complex* tasks like classification and regression
2. Neural Networks $\longrightarrow$ Non linear functions of an input x, given by $y(x) = \sigma\{\mathbf{w} \cdot x + b\}$
3. Rely on comparison with data $\longrightarrow$ *Learning*, need for training $\mathbf{w}$, b

The N3PDF project

What we actually measure

Any theory must predict a number $\longrightarrow$ Observable σ



Factorize the problem $\longrightarrow$ Convolute the PDFs with the partonic $\hat{\sigma}_{ij}$

$$\sigma = \int_0^1 dx_1\, dx_2\, f_\alpha(x_1, \mu_F) * f_\beta(x_2, \mu_F) * \hat{\sigma}_{\alpha\beta}(\alpha_s(\mu_R), \mu_F)$$

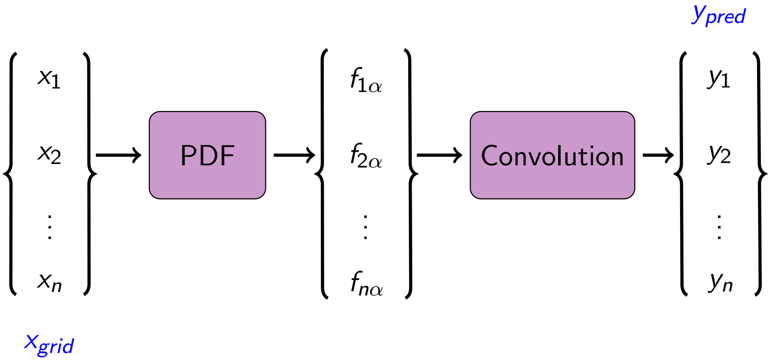
- Use a Neural networks to generate the PDFs
- Generate a vector of observables y_N

$$y_N = \sum_{i,j,\alpha,\beta} f_\alpha(x_i)\, f_\beta(x_j)\, \hat{\sigma}_{Nij\alpha\beta}$$

The N3PDF project

General structure of n3fit

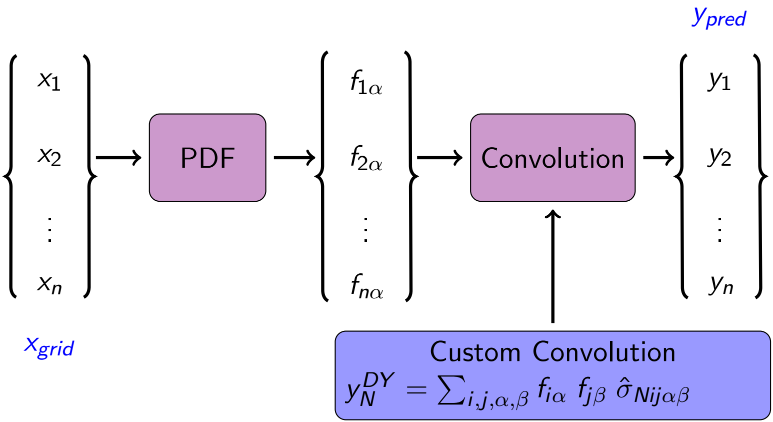
- Use TensorFlow and Keras to determine the PDFs
- See paper by S.Carraza - J.Cruz-Martinez
  "Towards a new generation of parton densities
  with deep learning models",
  https://arxiv.org/abs/1907.05075



1. Build a NN to compute y_{pred} observables from a grid x_i
2. Compute loss function by comparing with data
3. Update values of PDF $\longrightarrow$ Fit

The N3PDF project

Operator implementation



1. TF relies in symbolic computation $\longrightarrow$ High memory usage
2. Implement c++ operator replacing the convolution

DIS:

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

Results

Checking computation

Hadronic:

	TensorFlow	Custom	Ratio
	8.142365	8.142366	1.0000001
Convolution	8.947762	8.947762	1.0000000
	7.4513326	7.4513316	0.9999999
	18.525095	18.525095	1.0000000
Gradient	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

1. PDFs are required to have accurate predictions in high energy physics
2. ML provides a new way of determine the PDFs
3. Operator implementation leads to memory saving by taking full control on the computation

Thank you!

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