Theoretical physics, Machine Learning and Bioinformatics

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Milan, March 2021

This project has received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No 740006.

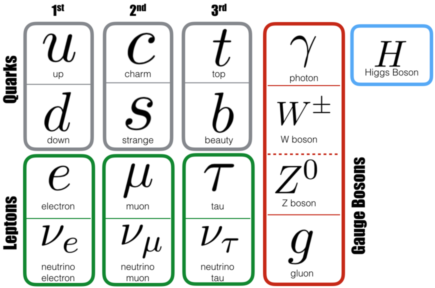
Outline

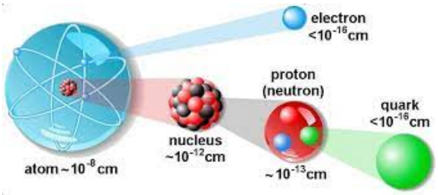
1. QCD in a nutshell
   - The fundamental interactions
   - Exploring matter at the small scales
   - Hadronic physics and the LHC
2. Machine Learning for particle physics
   - Machine Learning algorithms
   - NN for building predictions
3. Bioinformatics
   - Applying data sciences to life sciences
4. Summary

Quantum Chromodynamics in a nutshell

QCD in a nutshell

The Standard Model





Quantum Field Theory describing physics at the TeV scale $\rightarrow$ less than a fermi!

1. Fermions (quarks and leptons) composing matter
2. Bosons mediating interactions
3. Scalar Higgs field generating mass

Quantum Chromodynamics is the theory describing the strong interactions

QCD in a nutshell

Explore the strong interactions

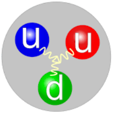
How to explore proton's inner structure?

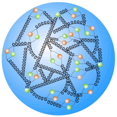
- Point-like projectile on the object $\longrightarrow$ DIS
- Smash the two objects $\longrightarrow$ LHC physics

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

QCD in a nutshell

Parton Distribution Functions





- Hadrons made of constantly interacting partons $\longrightarrow$ non perturbative physics
- Parton distribution functions (PDFs) are required for the precision era of the LHC
- PDFs can not be predicted yet not measured $\longrightarrow$ extracted from data via Machine Learning algorithms

Machine Learning for particle physics

Machine learning

What is Machine Learning?

1. Machine Learning algorithms are a subset of Artificial Intelligence (AI) algorithms
2. Used to solve *complex* tasks like classification, regression and pattern recognition
3. Rely on comparison with data $\longrightarrow$ Learning

The N3PDF project

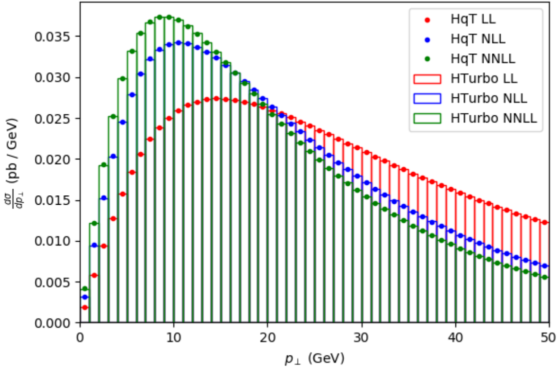
General structure of n3fit

Parton Distribution Functions (PDFs) can not be predicted or measured
PDFs need to be extracted from data!

- Use TensorFlow and Keras to determine the PDFs using neural networks
- Use Stochastic Gradient Descent n3fit replacing primitive fitting algorithms
- 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
- Operator Implementation in TF - Urtasun-Elizari et al.
  "Towards hardware acceleration for parton densities estimation",
  https://arxiv.org/abs/1909.10547

The HTurbo project

Comparison HRes and HqT - all orders



- Older codes (**HRes**, **HqT**) need 3 days to produce NNLL distribution
- 3 minutes with **HTurbo**! ✓
- Agreement up to NNLL $\longrightarrow$ ready for N^3LL

Bioinformatics
and
data science for life sciences

Bioinformatics

Comoputer sciences

- C++ and computer sciences
  - [https://github.com/JesusUrtasun/CppCourse]
- Machine Learning
  - [https://github.com/JesusUrtasun/MLcourse]
- Data Frames (Numpy, Pandas) and R programming
  - [https://github.com/JesusUrtasun/Bioinformatics]

- NGS data analysis
- Statistics and data analysis of BAM files with R
- **Rsubred** and **Dseq2** packages
- Fast learner!

Bioinformatics

DNA and RNA sequencing data

- NGS data analysis
- Statistics and data analysis of BAM files with R
- **Rsubred** and **Dseq2** packages
- Fast learner!

Summary & Conclusions

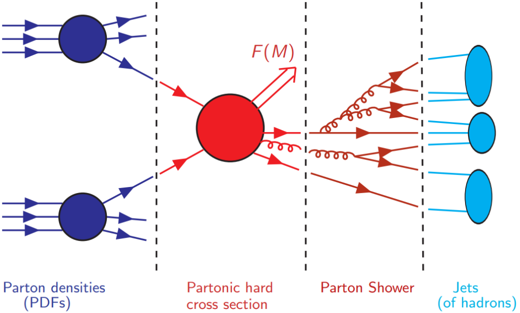
1. Precise knowledge of sub-nuclear interactions are required towards the precision era of the LHC
2. Machine Learning models provide a robust way for PDFs determination optimized through operator implementation in TF
3. We develop a numerical code **HTurbo**, implementing $q_{\perp}$ resummation for Higgs boson production, which is faster than any of the existing codes
4. Experience with Python and R for NGS data, and still looking to improve!

Thank you!

Back up

Hadronic collisions

Hadronic Physics $h_1(p_1) + h_2(p_2) \to F + X$

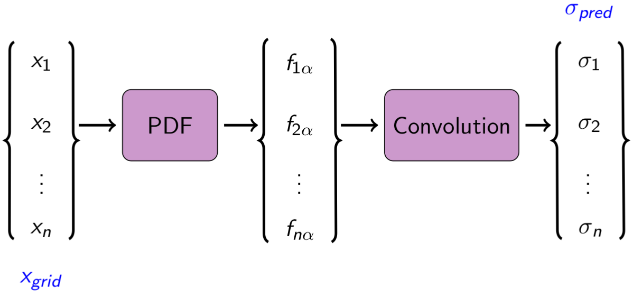


Factorize process as PDFs and partonic (hard) interaction

$$\sigma^{\mathrm{F}}(p_1, p_2) = \sum_{\alpha,\beta} \int_0^1 dx_1 dx_2 \; f_{\alpha/h_1}(x_1, \mu_F^2) * f_{\beta/h_2}(x_2, \mu_F^2) \; * \; \hat{\sigma}^{\mathrm{F}}_{\alpha\beta}(x_1 p_1, x_2 p_2, \alpha_s(\mu_R^2), \mu_F^2)$$

Back up

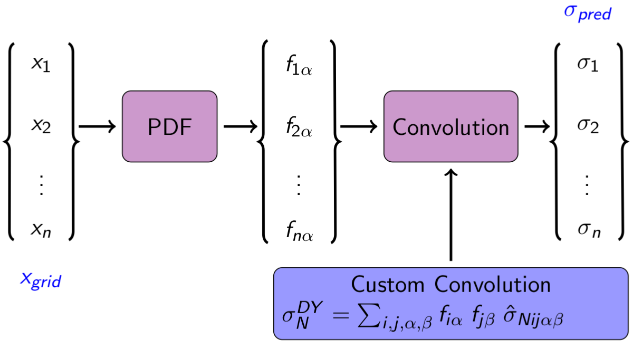
Operator implementation in TF



- Build a NN model to compute σ_{pred} observables from a grid x_i
- Perform χ^2 minimization comparing with data
- Update values of PDF $\longrightarrow$ Fit

The N3PDF project

Operator implementation in TF

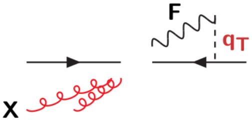


1. TF relies in symbolic computation $\longrightarrow$ High memory usage
2. Implement c++ operator replacing the convolution
3. Further details in Urtasun-Elizari et al.
   "Towards hardware acceleration for parton densities estimation", https://arxiv.org/abs/1909.10547

HTurbo

All order $q_\perp$ resummation

Study the differential $q_\perp$ distribution



$$h_1(p_1) + h_2(p_2) \longrightarrow F(M, {\color{red} q_\perp}) + X$$

$$\int_0^{Q_\perp^2} dq_\perp^2 \frac{d\hat{\sigma}}{dq_\perp^2} \sim c_0 + \alpha_s(c_{12}L^2 + c_{11}L + c_{10}) + ..., \quad \text{being} \quad L = \ln(q_\perp/M^2)$$

$\alpha_S L^2$	$\alpha_S L$	$\cdots$	$\mathcal{O}(\alpha_S)$
$\alpha_S^2 L^4$	$\alpha_S^2 L^3$	$\cdots$	$\mathcal{O}(\alpha_S^2)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$
$\alpha_S^n L^{2n}$	$\alpha_S^n L^{2n-1}$	$\cdots$	$\mathcal{O}(\alpha_S^n)$
dominant logs	$\cdots$	$\cdots$	$\cdots$

Truncated fixed order predictions lead to logarithmic enhancement $\alpha_s^n \ln^m(M^2/q_\perp^2)$

All order resummation is needed

HTurbo

Starting point: DYTurbo

$q_\perp$ resummation implemented in numerical codes **HqT** and **HRes** [Catani et al.]
Higher order accuracy require high computation times

Numerical code **DYTurbo** [Camarda et al. ATLAS collaboration, 1910.07049], fast and precise $q_\perp$ resummation and several improvements for Drell-Yan $(h_1 + h_2 \to V + X \to l^+ l^- + X)$

- Goal: set up a numerical code generalizing **DYTurbo** for Higgs boson production
- Goal: extend theoretical accuracy up to N^{3}LL+N^{3}LO and to other processes

Numerical code **HTurbo** [Ferrera, Urtasun-Elizari (in preparation)]
Fast and precise $q_\perp$ resummation and for Higgs boson production

- Old versions as **HqT** and **HRes** in Fortran
- c++ allows for optimization in the integration routines