Gaussian Process for the estimation of theory uncertainties

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N3PDF Machine Learning • PDFs • QCD

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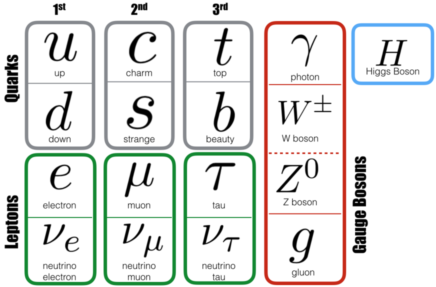
Outline

1. QCD in a nutshell
   - The Standard Model of particle physics
   - LHC physics and theory uncertainties
   - Factorization theorem
2. Machine Learning
   - Motivation for Machine Learning
   - Neural Networks & general strategy
3. Gaussian Process and theory uncertainties
   - The N3PDF project
   - Kernel based methods
   - Results & Conclusions

QCD in a nutshell

The Standard Model

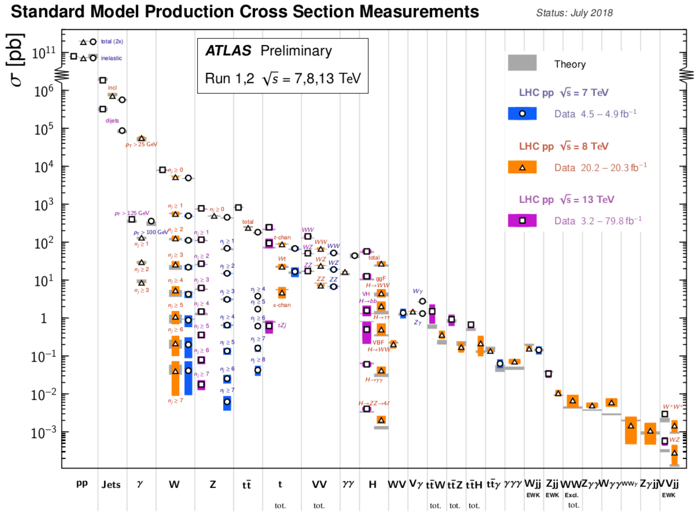


Quantum Field Theory describing physics at the TeV scale

- Fermions composing matter (leptons and quarks)
- Bosons as mediators of the interactions
- Scalar Higgs generating mass

QCD in a nutshell

LHC physics



QCD in a nutshell

Explore the strong interactions

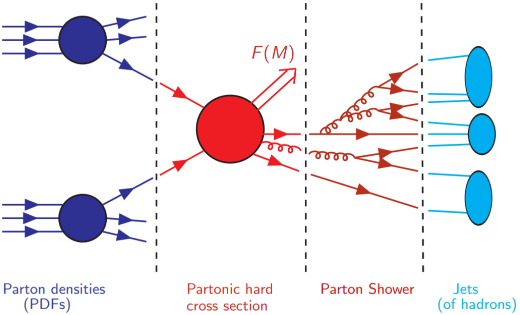
How to explore proton's inner structure?

- 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

Factorization theorem



Compute cross sections is a hard problem $\longrightarrow$ QCD Factorization

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

Machine learning

What is Machine Learning?

1. A subset of Artificial Intelligence (AI) algorithms
2. Used to solve *complex* tasks like classification and regression
3. Rely on comparison with data $\longrightarrow$ Learning through minimization of some loss function

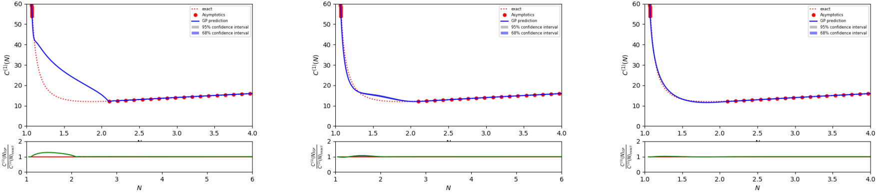
The N3PDF project

Machine Learning for subnuclear structure

1. Take the asymptotics of $\hat{\sigma}(N)$ computed by following 1303.3590 as input (training) data.
2. Assume the points are sampled from a Gaussian distribution $f(x) \sim N(\mu, K(\Theta, x, x'))$.
3. Train Θ by minimizing a $\chi^2(f(x)|\Theta, x)$ to guess the underlying law through exhaustive search $\longrightarrow$ hyperoptimization
4. Use the Mellin-space exact coefficient functions computed by ggHiggs as true values for testing and validation.

Results

Learning a physical quantity



- Combination of different kernels leads to better fit
- Excellent numerical agreement up to N3LO

When there is not theory prediction to compare to, use GP approach to estimate theory uncertainty

Summary & Conclusions

1. Precise predictions are required towards precision era of the LHC
2. ML provides an effective way of fitting a curve
3. Kernel-based methods particularly powerful for interpolation
4. Theory uncertainty can be extracted from the confidence interval given by the Gaussian Process

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