Gaussian Process for the estimation of theory uncertainties

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N3PDF Machine Learning • PDFs • QCD

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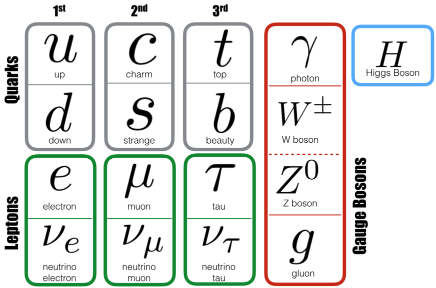
Outline

1. QCD in a nutshell
   - The Standard Model & strong interactions
   - Parton Distribution Functions
   - Factorization theorem
2. Machine Learning
   - Motivation for Machine Learning
   - Neural Networks & general strategy
3. Gaussian Process and theory uncertainties
   - The NNPDF methodology
   - Operator implementation in TensorFlow
   - Results & Conclusions

QCD in a nutshell

The Standard Model



Quantum Field Theory describing physics at the TeV scale

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

QCD in a nutshell

Explore the strong interactions

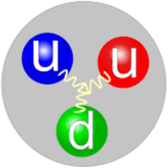
How to explore proton's inner structure?

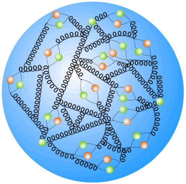
- Point-like projectile on the object $\longrightarrow$ DIS
- Smash the two objects $\longrightarrow$ LHC physics

"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





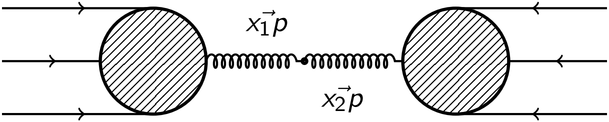
- Hadrons made of partonic objects $\longrightarrow$ non perturbative physics
- Interactions take place only at partonic level

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

QCD in a nutshell

Factorization theorem

Observables in hadronic events $\longrightarrow$ σ is hard to compute



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

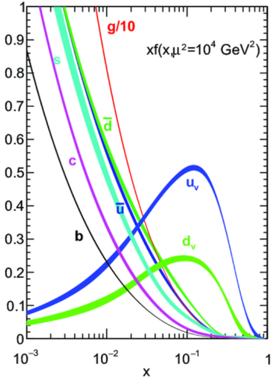
$$\sigma = \int_0^1 dx_1\ dx_2\ f_\alpha(x_1, \mu_F) * f_\beta(x_2, \mu_F) * \hat{\sigma}_{\alpha\beta}(\alpha_s(\mu_R), \mu_F)$$

- Partonic $\hat{\sigma}$ can be computed as perturbative series in α_s
- PDFs absorb the non perturbative effects, evaluated at μ_F

QCD in a nutshell

What PDFs look like

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



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

The N3PDF project

Fitting a PDF

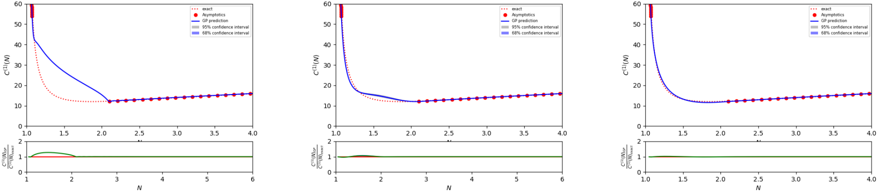
Factorize the problem $\longrightarrow$ Convolute the PDFs with the partonic $\hat{\sigma}_{ij}$

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

- Partonic $\hat{\sigma}_{\alpha\beta}$ is computed perturbatively. Hadronic σ is measured.
- Use a Neural Networks to generate (*fit*) the PDFs
- Generate a vector of observables σ_N to be compared with data

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

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. PDFs are required to have accurate predictions in high energy physics
2. ML provides an effective way of fitting a curve
3. Theory uncertainty can be extracted from the confidence interval given by the Gaussian Process

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