

Gaussian Process for the estimation of theory uncertainties

Jesús Urtasun Elizari

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Outline

① QCD in a nutshell

- The Standard Model of particle physics
- QCD and strong interactions
- Factorization theorem

② Machine Learning

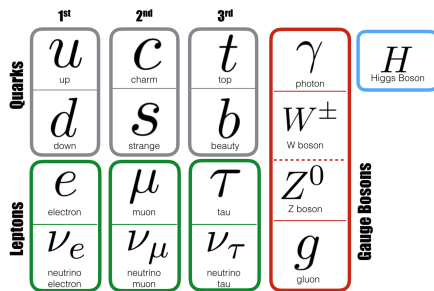
- Motivation for Machine Learning
- Neural Networks & general strategy

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?

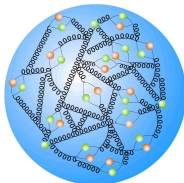
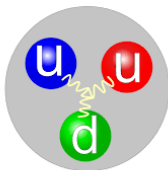


- Point-like projectile on the object \rightarrow DIS
- Smash the two objects \rightarrow LHC physics

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

QCD in a nutshell

Parton Distribution Functions



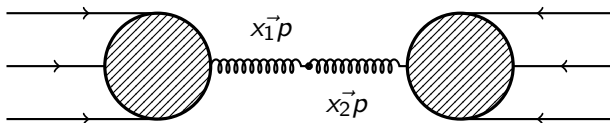
- Hadrons made of partonic objects \longrightarrow non perturbative physics
- Interactions take place only at partonic level

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 $\longrightarrow \sigma$ 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

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 → **Learning**



The N3PDF project

Fitting a PDF

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

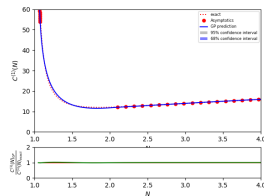
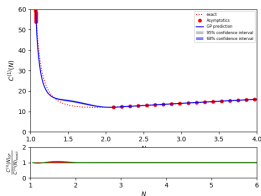
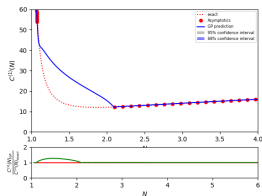
$$\sigma = \int_0^1 dx_1 dx_2 f_{\alpha}(x_1, \mu_F) * f_{\beta}(x_2, \mu_F) * \hat{\sigma}_{\alpha\beta}(\alpha_s(\mu_R), \mu_F)$$

- 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

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

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 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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