High precision perturbative QCD predictions for LHC physics

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DI MILANO

N3PDF
Machine Learning • PDFs • QCD

European
Research
Council

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Outline

QCD factorization in a nutshell

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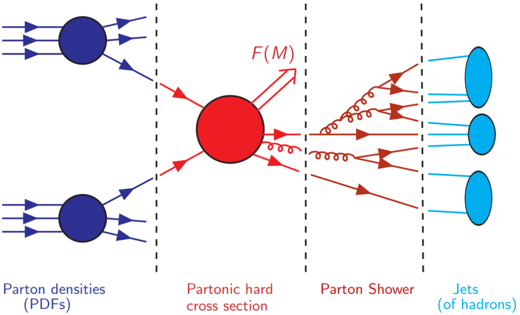
Factorization theorem

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



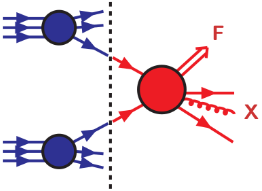
Factorize process as PDFs and partonic (hard) interaction

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

QCD factorization in a nutshell
Perturbative QCD

Precise QCD predictions require precise knowledge of PDFs and partonic cross section $\hat{\sigma}$

- Born cross section is the leading-order (LO) term of the perturbative series
- $\sigma^{(1)}, \sigma^{(2)}, \sigma^{(3)}$ are the NLO, NNLO, N^{3}LO corrections



$$\hat{\sigma} = \sigma^{\text{Born}}\left(1 + \alpha_s \sigma^{(1)} + \alpha_s^2 \sigma^{(2)} + \alpha_s^3 \sigma^{(3)} + \ldots\right)$$

LO predictions strongly depend on unphysical renormalization and factorization scales
Need higher order corrections to increase theoretical accuracy!

The N3PDF project

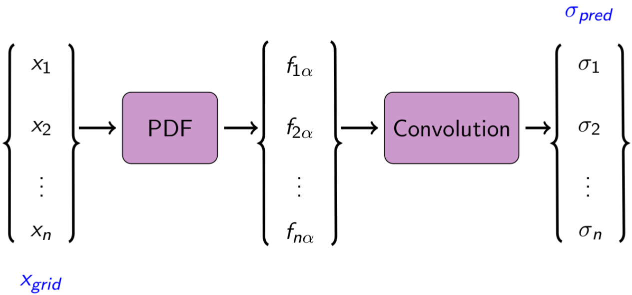
The N3PDF project

General structure of n3fit

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

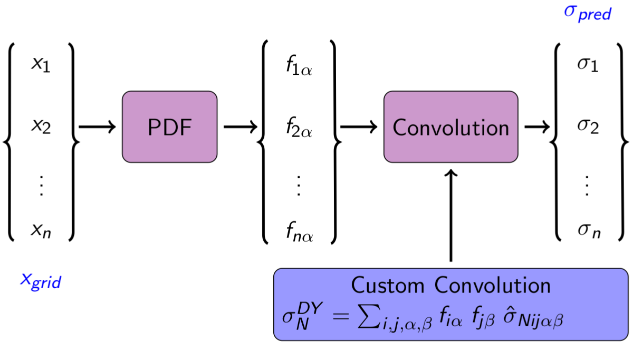
- Use TensorFlow and Keras to determine the PDFs
- Use Stochastic Gradient Descent n3fit replacing primitive genetic algorithms
- See paper by S.Carraza - J.Cruz-Martinez
  "Towards a new generation of parton densities with deep learning models",
  https://arxiv.org/abs/1907.05075

Neural Network model for PDF fits $\longrightarrow$ n3fit



- 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

Neural Network model for PDF fits $\longrightarrow$ n3fit



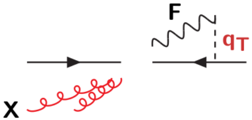
1. TF relies in symbolic computation $\longrightarrow$ High memory usage
2. Implement c++ operator replacing the convolution
3. Further details in Urtasun-Elizari et al.
   "Towards hardware acceleration for parton densities estimation",
   https://arxiv.org/abs/1909.10547

HTurbo: Fast predictions for resummed distributions

HTurbo

All order $q_\perp$ resummation

Study the differential $q_\perp$ distribution



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

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

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

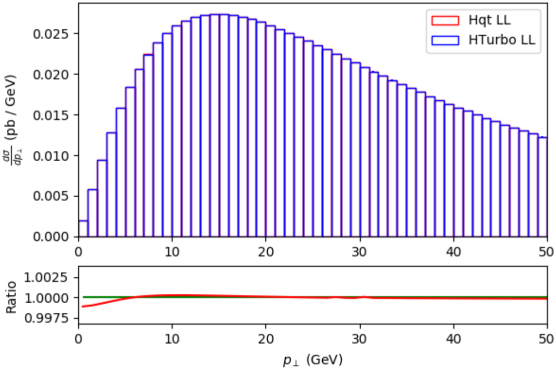
Numerical code **DYTurbo** [Camarda et al. ATLAS collaboration, 1910.07049], fast and precise $q_\perp$ resummation and several improvements for Drell-Yan $(h_1 + h_2 \to V + X \to l^+ l^- + X)$

- 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

Preliminary results to be seen in [Ferrera, Urtasun-Elizari.]

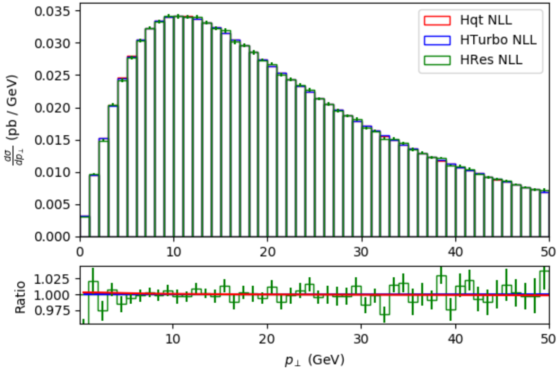
Results

Comparison with HRes and HqT - LL



- HTurbo $q_\perp$ distribution vs HRes and HqT at LL
- Excellent numerical agreement up to the 0.1% level ✓

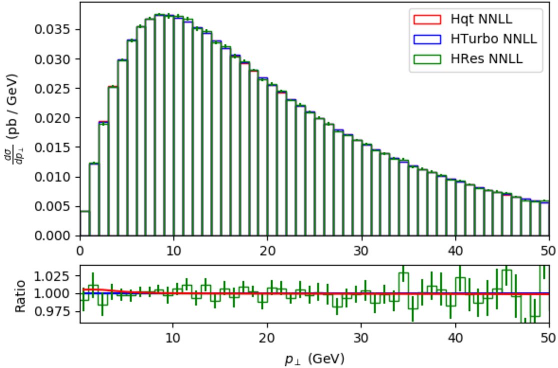
Comparison with HTurbo and HqT - NLL



- HTurbo $q_\perp$ distribution vs HRes and HqT at NLL
- Excellent numerical agreement up to the 0.1% level ✓

Results

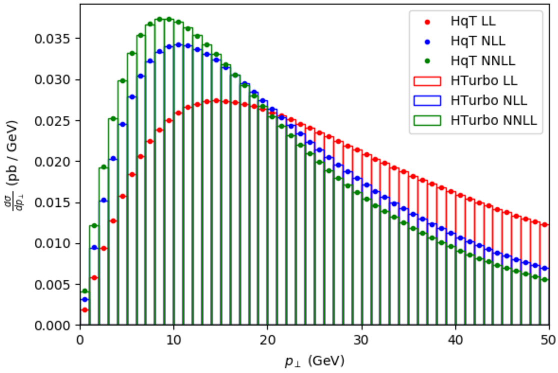
Comparison with HRes and HqT - NNLL



- HTurbo $q_\perp$ distribution vs HRes and HqT at NNLL
- Excellent numerical agreement up to the 0.1% level ✓

Results

Comparison HRes and HqT - all orders



- Higher orders lead to more accurate predictions ✓
- **HRes** needs 3 days to produce NNLL distribution → 3 minutes with **HTurbo**! ✓
- Agreement up to NNLL ⟶ ready for N^{3}LL

Summary & Conclusions

1. Precise knowledge of PDFs and partonic cross sections 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. Next steps:
    - Validate results at NNLO
    - Include full N^3LO prediction
    - Perform phenomenological studies comparing with LHC data

Thank you!

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