



# PROTON STRUCTURE FROM ARTIFICIAL INTELLIGENCE TO MACHINE LEARNING

### STEFANO FORTE

Università di Milano & INFN







PPT SEMINAR

OXFORD, MAY 21, 2020





### MACHINE LEARNING THE UNKNOWN

### STEFANO FORTE

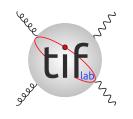
Università di Milano & INFN

**GUEST STAR:** 

### LUKAS HENNING

**FREIBURG** 







### SUMMARY UNCERTAINTIES

- UNCERTAINTIES AND PDFS
- NOW, AND TOMORROW
- THE PROBLEMS OF PDF UNCERTAINTIES

#### ARTFICIAL INTELLIGENCE

- THE NNPDF METHODOLOGY
- CLOSURE TESTS

#### MACHINE LEARNING

- AI VS. ML
- HYPEROPTIMIZATION
- TESTING

#### LEARNING LEARNING

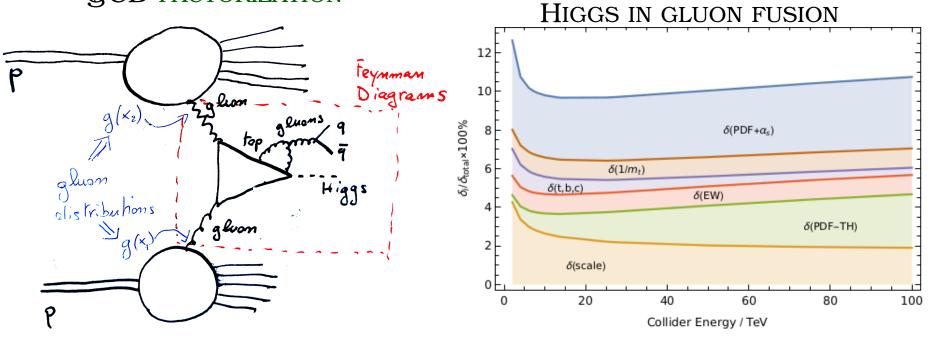
- K-FOLDING
- GAUSSIAN PROCESSES
- TRANSFER LEARNING

### **UNCERTAINTIES**

### **UNCERTAINTIES AND PDFs**



#### **UNCERTAINTIES:**

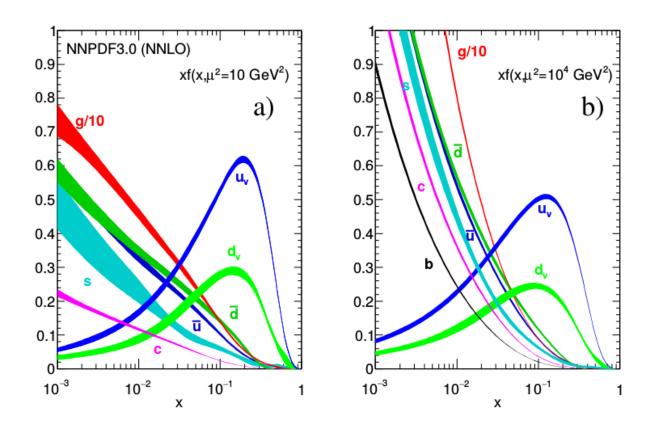


(HL-LHC Higgs WG report, 2019)

- PDF ESPRESS THE LIKELIHOOD OF A QUARK OR GLUONS (PARTONS)
  TO ENTER A COLLISION
- THEIR KNOWLEDGE IS A DOMINANT SOURCE OF UNCERTAINTY

### A PORTRAIT OF THE PROTON

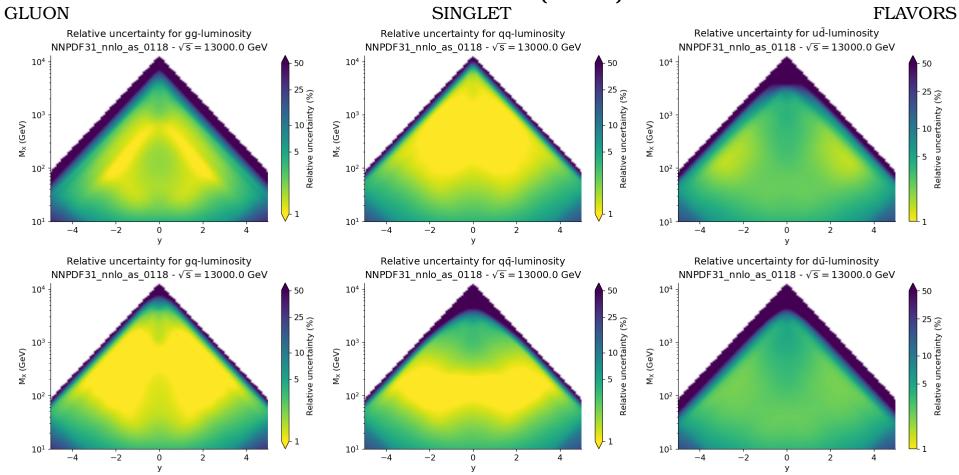
### AS SEEN FROM A HIGGS BOSON



(PDG 2018)

- PARTON DISTRIBUTIONS: MOMENTUM FRACTION DISTRIBUTIONS FOR EACH TYPE OF QUARK, ANTIQUARK & THE GLUON
- EXTRACTED FROM DATA, COMPARING PDF-DEPENDENT PREDICTION & INVERTING
- MUST DETERMINE A PROBABILITY DISTRIBUTION OF FUNCTIONS FROM A DISCRETE SET OF DATA
- TYPICAL UNCERTAINTIES (PDF4LHC15): 3-5%

### PDF UNCERTAINTIES: NOW NNPDF3.1 NNLO (2017)

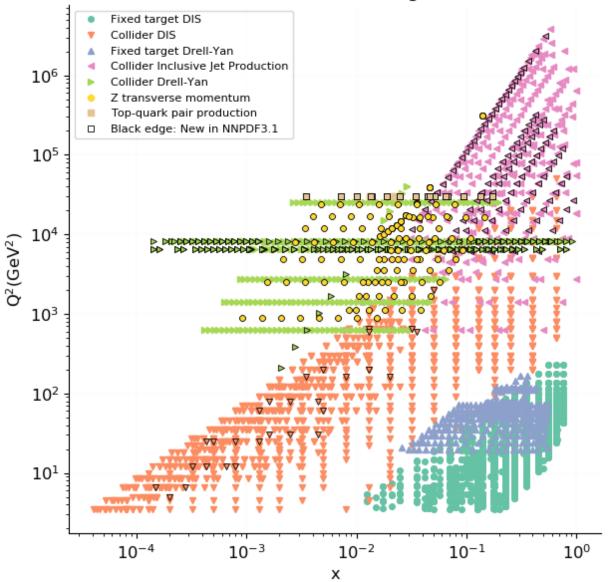


- TYPICAL UNCERTAINTIES IN DATA REGION  $\sim 1-3\%$
- SWEET SPOT: VALENCE Q G; 1% OR BELOW

CT18 (Dec 2019): SOMEWHAT SMALLER DATASET, RATHER LARGER UNCERTAINTIES

### DATASET WIDENING NNPDF3.0 vs NNPDF3.1 (CT14 vs. CT18: SIMILAR)

#### Kinematic coverage



#### NEW DATA: (BLACK EDGE)

- HERA COMBINED  $F_2^b$
- DO W LEPTON ASYMMETRY
- ATLAS W, Z 2011, HIGH & LOW MASS DY 2011; CMS  $W^{\pm}$  RAPIDITY 8TEV LHCB W, Z 7TEV & 8TEV
- ATLAS 7TeV JETS 2011, CMS 2.76TeV JETS
- ATLAS & CMS TOP DIFFERENTIAL RAPIDITY
- ATLAS Z  $p_T$  DIFFERENTIAL RAPIDITY & INVARIANT MASS 8TeV, CMS Z  $p_T$  DIFFERENTIAL RAPIDITY 8TeV

### DATASET WIDENING NNPDF4.0 SUMMARY (EXPECTED IN 2020)

- 1. OLD DATASETS WITH IMPROVED TREATMENT
  - ASSORTED DEBUGGING
  - CORRELATIONS IN ATLAS TOP DISTRIBUTIONS AT 8 TEV
  - CHOICE OF SCALE AND CORRELATION MODELS FOR SINGLE-JET DATA
  - MASSIVE CORRECTIONS TO NEUTRINO DIS DIMUON CROSS SECTIONS AT NNLO
  - NUCLEAR UNCERTAINTIES IN FIXED-TARGET DIS AND DY
- 2. New datasets for old processes
  - DIS c and b production (HERA combined)
  - SINGLE JET PRODUCTION (ATLAS, CMS)
  - TOP PAIR PRODUCTION (ATLAS, CMS)
  - COLLIDER DY/INCLUSIVE VECTOR BOSON PRODUCTION (ATLAS, CMS, LHCB)
  - COLLIDER VECTOR BOSON PRODUCTION IS ASSOCIATION WITH CHARM ( CMS)
- 3. New datasets for new processes
  - ISOLATED PHOTON PRODUCTION (ATLAS)
  - SINGLE TOP PRODUCTION (ATLAS, CMS)
  - COLLIDER DIJET PRODUCTION (ATLAS, CMS)
  - DIS+JET(S) PRODUCTION (H1, ZEUS)
  - COLLIDER VECTOR BOSON PRODUCTION IS ASSOCIATION WITH JETS (ATLAS, CMS)

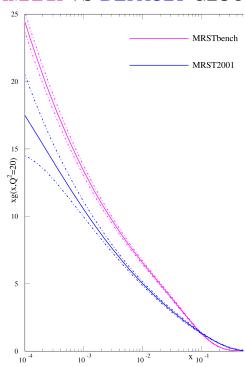
 $\mathcal{O}(50)$  NEW/REVISED DATASETS

TOWARDS SUBPERCENT UNCERTAINTIES??!!

### THE PDF UNCERTAINTY PROBLEM: THE HERA-LHC BENCHMARK (2005)

- RESTRICTED AND VERY CONSISTENT DATASET USED
- RESULTS COMPARED TO THEN-BEST RESULT FROM FULL DATASET

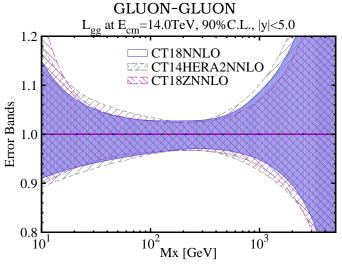
#### BENCHMARK VS DEFAULT GLUON

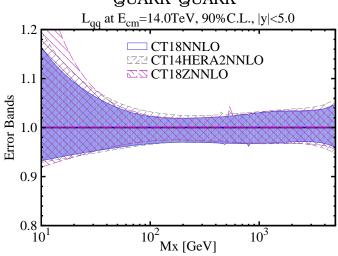


"...the partons extracted using a very limited data set are completely incompatible, even allowing for the uncertainties, with those obtained from a global fit with an identical treatment of errors...The comparison illustrates the problems in determining the true uncertainty on parton distributions." (R.Thorne, HERALHC, 2005)

### THE PDF UNCERTAINTY PROBLEM: UNCERTAINTY REDUCTION?

CT18 VS. CT14: PARTON LUMINOSITY UNCERTAINTIES QUARK-QUARK





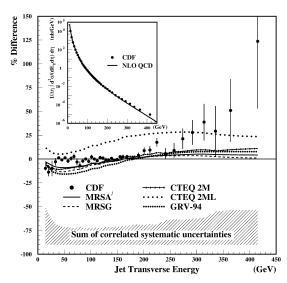
### MORE DATA ⇒ BIGGER UNCERTAINTIES (?!) PARTON PARAMETRIZATIONS

- CTEQ5 2002:  $xg(x, Q_0^2) = A_0 x^{A_1} (1-x)^{A_2} (1+A_3 x^{A_4})$
- $\bullet \ \ \text{MRST-HERALHC 2005:} \ xg(x,Q_0^2) = A_g x^{\delta g} (1-x)^{\eta g} (1+\epsilon_g x^{0.5} + \gamma_g x) + A_{g'} x^{\delta g'} (1-x)^{\eta_g'} x^{\delta g'} x^{\delta g'} (1-x)^{\eta_g'} x^{\delta g'} x^{\delta g$
- CT18:  $g(x, Q = Q_0) = x^{a_1 1} (1 x)^{a_2} [a_3 (1 y)^3 + a_4 3y (1 y)^2 + a_5 3y^2 (1 y) + y^3];$  $y = \sqrt{x}; a_5 = (3 + 2a_1)/3.$

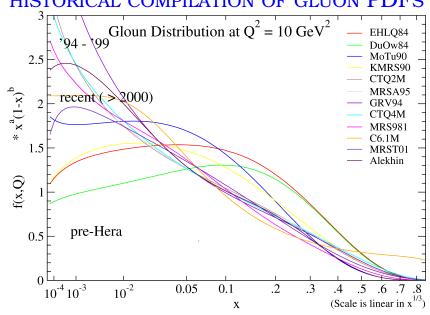
#### BIAS?

### THE PROBLEM OF LARGE-x INTERPOLATION

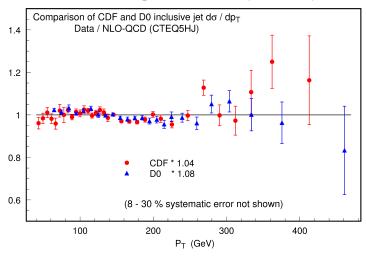
- DISCREPANCY BETWEEN QCD CALCULATION AND CDF JET DATA (1995)
- EVIDENCE FOR QUARK COMPOSITENESS?
- RESULT STRONGLY DEPENDS ON GLUON AT  $x \gtrsim 0.1$
- PDF MUST VANISH AT x = 0, BUT (THEN) NO DATA FOR  $x \ge 0.05$ !



### DISCREPANCY REMOVED IF JET DATA USED FOR GLUON DETERMINATION HISTORICAL COMPILATION OF GLUON PDFS



#### NEW CTEQ GLUON (1998)

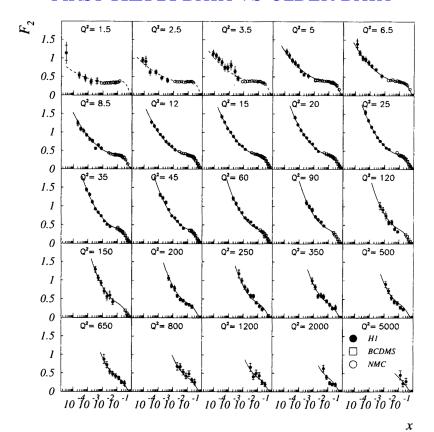


W.K.Tung, DIS 2004

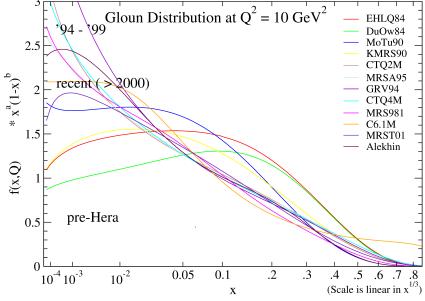
NOW: NO DATA FOR  $x \gtrsim 0.5 \Rightarrow$  DISCOVERY (THRESHOLD) REGION!

### THE PROBLEM OF SMALL-x EXTRAPOLATION

1995: THE RISE OF STRUCTURE FUNCTIONS AT HERA FIRST HERA DATA VS OLDER DATA







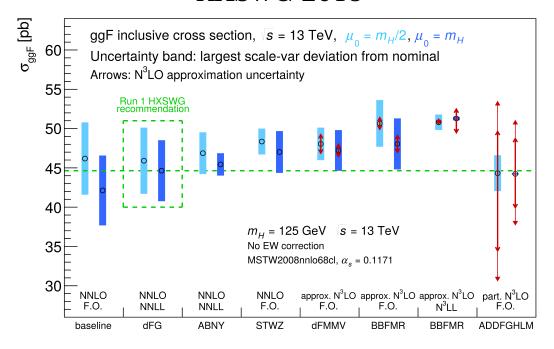
W.K.Tung, DIS 2004

A. de Roeck, Cracow epiphany conf. 1996

- RISE OF  $F_2$  AT HERA CAME  $\Rightarrow$  SURPRIZE
- HINTED BY PRE-HERA DATA; VETOED BY THEORETICAL BIAS

### THE PROBLEM OF MISSING HIGHER ORDERS

THE GLUON FUSION HIGGS CROSS SECTION: APPROXIMATE N<sup>3</sup>LO (LHC 13) HXSWG 2015



(ALMOST) EXACT N<sup>3</sup>LO (Anastasiou et al, 2016):  $48.58 \pm 1.4$ PB (MHO) (HXSWG, **2017**)

EXACT N<sup>3</sup>LO+N<sup>3</sup>LL+LLx:  $48.9 \pm 1.9$ PB (HL-LC AND HL-LHC YR, **2019**)

SCALE VARIATION? ENVELOPE? RESUMMATION? BIAS?

### BIAS?

#### **FRONIMO**

#### **DIALOGO**

by
VINCENTIO GALILEI
Noble Florentine

On the Art of Intabulating Well and Playing Music Correctly on Stringed Instruments as well as Winds, and in particular, on the Lute.

Newly reprinted, and enriched by the Author, and provided with new ideas and examples.

#### VENICE:

At the Shop of the Heir of Girolamo Scotto M. D. LXXXIV

## DI ALOGO DI VINCENTIO GALILEI NOBILE FIORENTINO

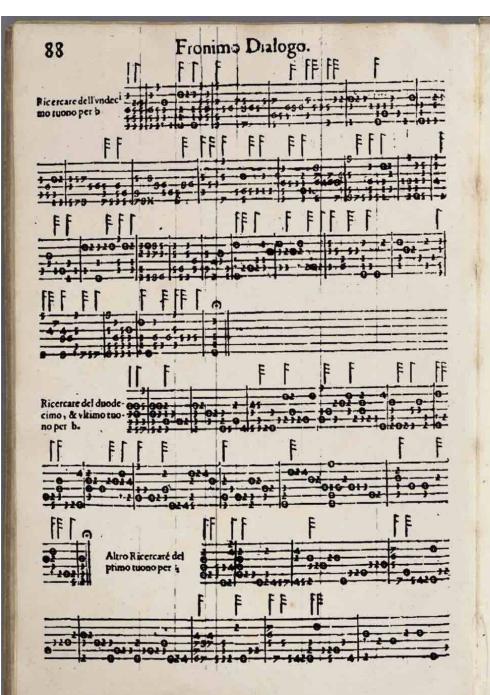
SOPRA L'ARTE DEL BENE INTAVOLARE,
ET RETTAMENTE SONARE LA MVSICA
Negli strumenti artificiali si di corde come di fiato; & in particulare nel Liuto,

Nuouamente ristampato, es dall'Autorè istesso arrichito es ornato dinouità di concetti, es d'essempi.



Appresso l'Hrede di Girolamo Scotto,

M. D. L X X X I I I I.



F sempio del fine de dodici Tuoni per b molle.



Eda confiderare ancora, che le modulationi de tuoni trasportati per h duro, sono naturali per b molle, & le trasportate di quello, sono naturali in quello, & per maggior notitia datui di esti tuoni, vi note-tò ancora per h duro, & per b molle nella parte del Tenore, & del Basso (secondo le chiati ioto ordinarie) la corda finale di ciascun Tuono, & sotto per più intelligenza vi allegherò di ciascun di esti vna Canzone, delle famose che così all'improniso mi souverranno, & saràno le sottoposte.

Essempio della corda finale del Tenore es del Basso di tutti i dodici Tuoni, ce per i duro, es per b molle.

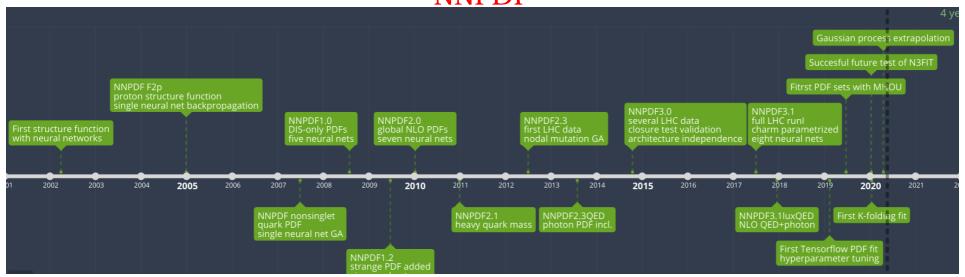


Del primo Tuono per a quadro-hauere Vergine bella di Cipriano nel fuo terzo libro a cinque voci, del fecondo Herbedi Prati dello Strigio nel fecondo fuo libro pute a cinque, del terzo tuono poi nel medicimo libro di Cipriano ci è Vergine fola nel primo libro a cinque dello Strigio, vi è del quarto tuono quella che comincia Che deggio fare del quinto tuono poi, hauete Dorna ch'ornata fete, di Cipriano nel primo fuo libro a quattro voci nel fecondo libro a fei voci dello Strigio.



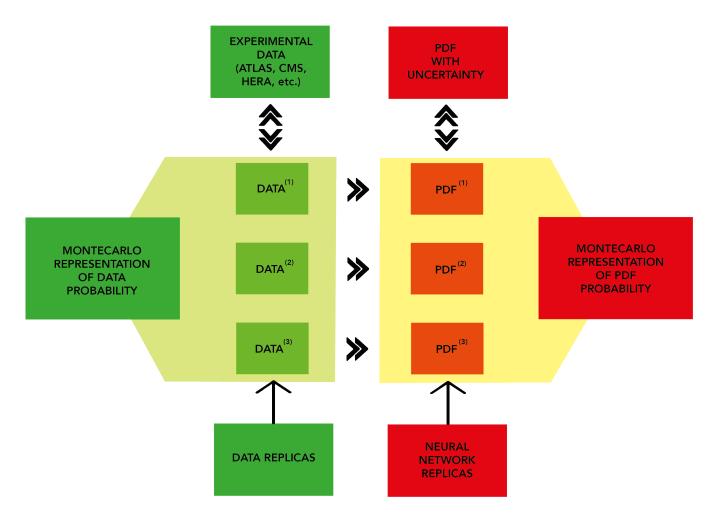
# OVERCOMING BIAS: PDFs FROM AI

### PROTON STRUCTURE AS AN AI PROBLEM: NNPDF



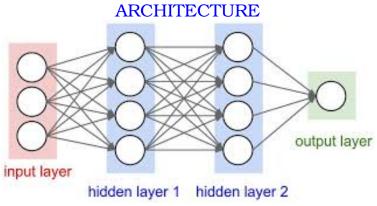
### AI FOR PDFS: THE NNPDF APPROACH THE FUNCTIONAL MONTE CARLO

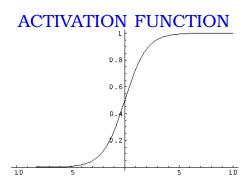
REPLICA SAMPLE OF FUNCTIONS ⇔ PROBABILITY DENSITY IN FUNCTION SPACE KNOWLEDGE OF LIKELIHHOD SHAPE (FUNCTIONAL FORM) NOT NECESSARY



FINAL PDF SET:  $f_i^{(a)}(x,\mu)$ ; i =up, antiup, down, antidown, strange, antistrange, charm, gluon;  $j = 1, 2, ... N_{\text{rep}}$ 

#### ARTIFICIAL INTELLIGENCE NEURAL NETWORKS





#### **PARAMETERS**

- WEIGHTS  $\omega_{ij}$
- THRESHOLDS  $\theta_i$

$$F_{\text{out}}^{(i)}(\vec{x}_{\text{in}}) = F\left(\sum_{j} \omega_{ij} x_{\text{in}}^{j} - \theta_{i}\right)$$

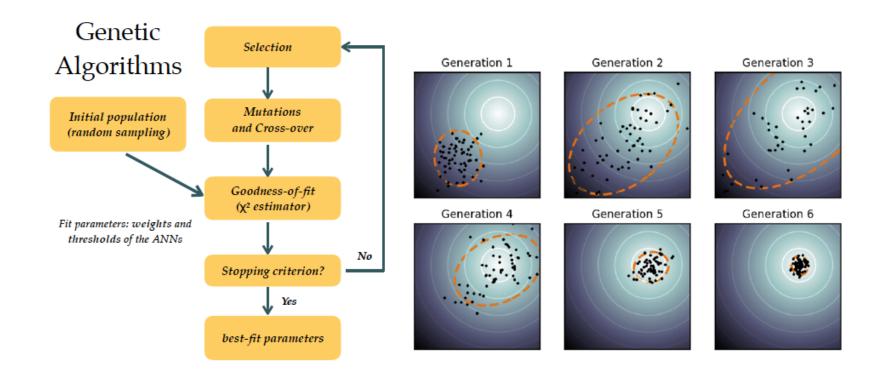
SIMPLEST EXAMPLE 1-2-1

$$f(x) = \frac{1}{\theta_1^{(3)} - \frac{\omega_{11}^{(2)}}{1 + e^{\theta_1^{(2)} - x\omega_{11}^{(1)}} - \frac{\omega_{12}^{(2)}}{1 + e^{\theta_2^{(2)} - x\omega_{21}^{(1)}}}}$$

NNPDF: 2-5-3-1 NN for each PDF:  $37 \times 8 = 296$  parameters

### SUPERVISED LEARNING GENETIC ALGORITHMS

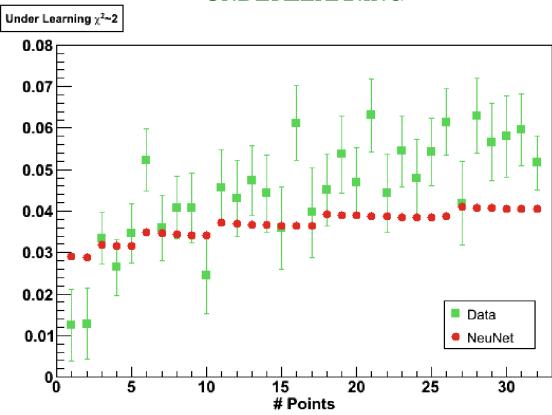
- BASIC IDEA: RANDOM MUTATION OF THE NN PARAMETER
- SELECTION OF THE FITTEST



### **NEURAL LEARNING**

- COMPLEXITY INCREASES AS THE FITTING PROCEEDS
- UNTIL LEARNING NOISE
- WHEN SHOULD ONE STOP?

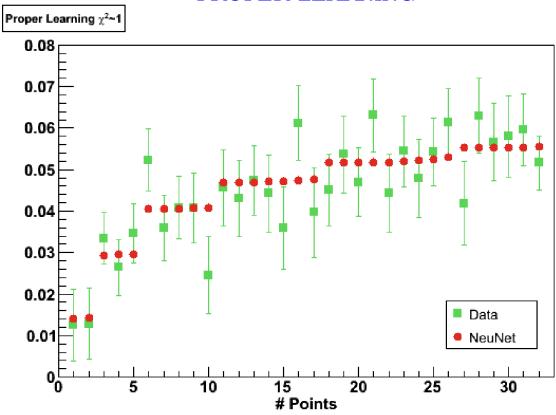
### UNDERLEARNING



### **NEURAL LEARNING**

- COMPLEXITY INCREASES AS THE FITTING PROCEEDS
- UNTIL LEARNING NOISE
- WHEN SHOULD ONE STOP?

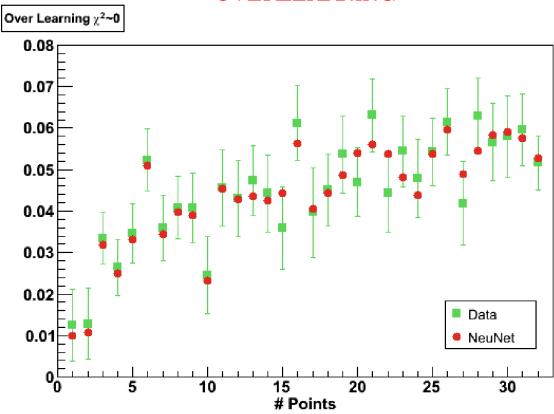
#### PROPER LEARNING



### **NEURAL LEARNING**

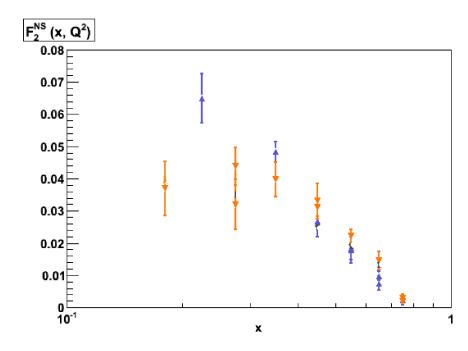
- COMPLEXITY INCREASES AS THE FITTING PROCEEDS
- UNTIL LEARNING NOISE
- WHEN SHOULD ONE STOP?





### GENETIC MINIMIZATION: AT EACH GENERATION, $\chi^2$ EITHER UNCHANGED OR DECREASING

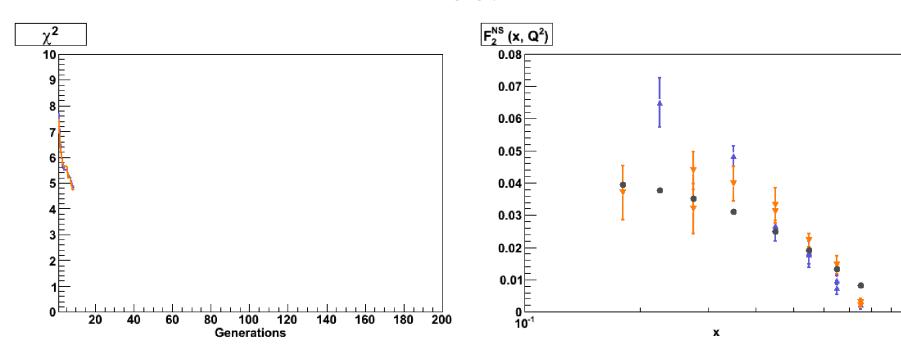
- DIVIDE THE DATA IN TWO SETS: TRAINING AND VALIDATION
- ullet MINIMIZE THE  $\chi^2$  OF THE DATA IN THE TRAINING SET
- ullet AT EACH ITERATION, COMPUTE THE  $\chi^2$  FOR THE DATA IN THE VALIDATION SET (NOT USED FOR FITTING)
- $\bullet$  WHEN THE VALIDATION  $\chi^2$  STOPS DECREASING, STOP THE FIT



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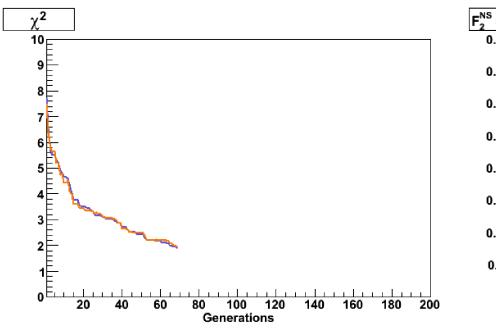
#### GO!

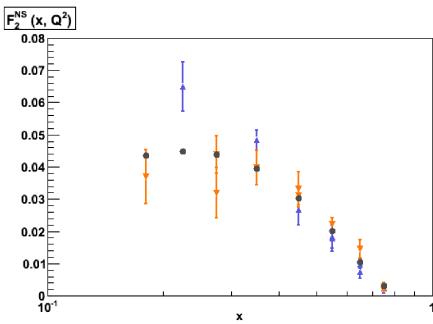


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#### STOP!

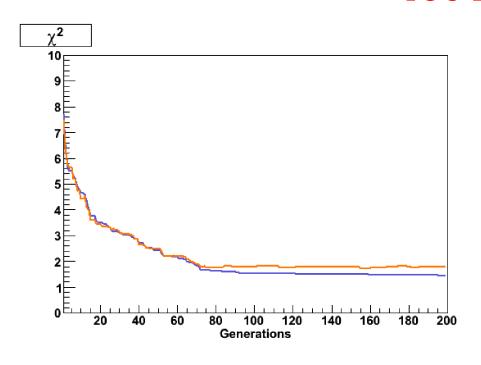


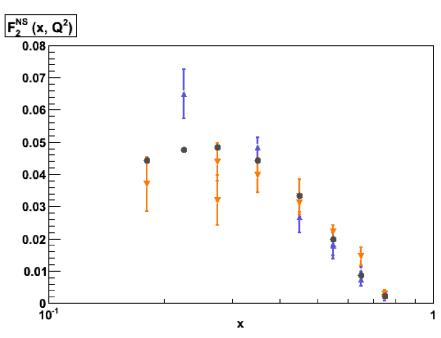


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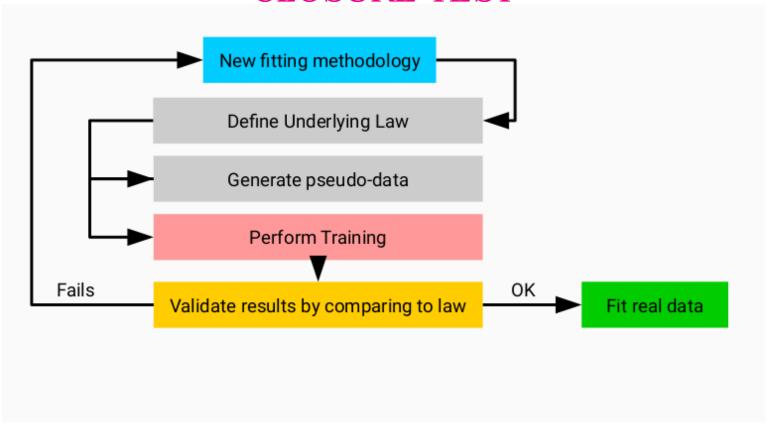
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#### TOO LATE!

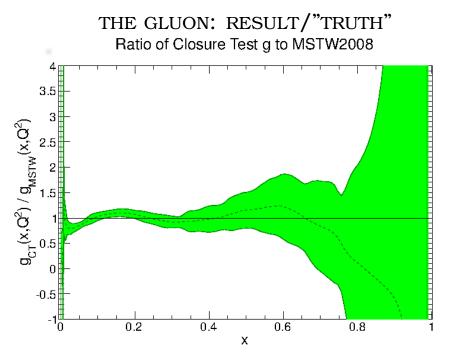


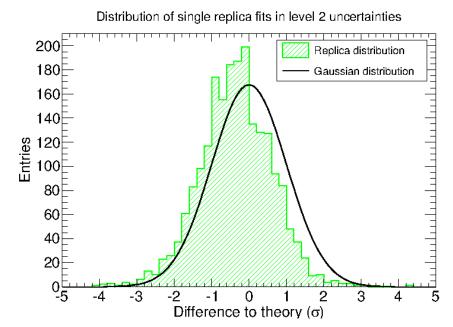


### HOW DO WE KNOW THAT WE GOT THE RIGHT ANSWER? CLOSURE TEST



### FIRST CLOSURE TEST (NNPDF3.0; 2014) NORMALIZED DISTRIBUTION OF DEVIATIONS





1  $\sigma$ : 70% (should be 68%)

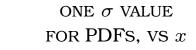
• THE METHODOLOGY IS FAITHFUL

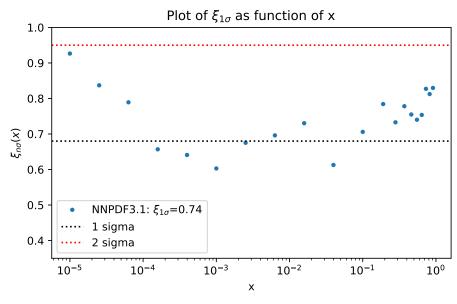
### LEARNING THE METHODOLOGY

### **CLOSURE TEST: A CLOSER LOOK (NNPDF3.1)**

ONE  $\sigma$ : ACTUAL/PREDICTED FOR DATA, BY EXPERIMENT

	NNPDF3.1 ratio
experiment	
NMC	0.882828
$\operatorname{SLAC}$	0.767063
BCDMS	0.730569
CHORUS	0.698907
NTVDMN	0.991090
HERACOMB	0.847359
HERAF2CHARM	1.867597
F2BOTTOM	1.124157
DYE886	0.655955
DYE605	0.585725
CDF	0.961652
D0	0.881199
ATLAS	0.904127
CMS	1.090241
LHCb	1.092194
Total	0.842168





- UNCERTAINTIES OVERESTIMATED
- 1  $\sigma$ >68% at very small and very large x; 1  $\sigma$  <68% at intermediate x

### CAN WE DO BETTER?

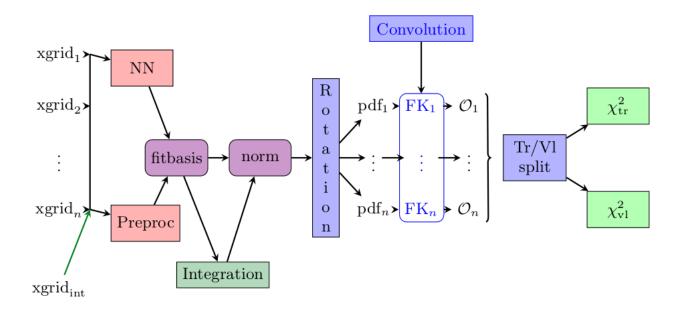
#### LEARNING THE METHODOLOGY



### THE N3FIT PROJECT

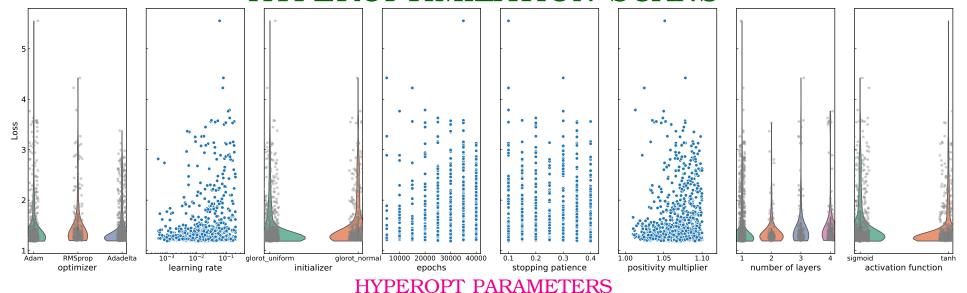
HOW DO WE KNOW THAT THE METHODOLOGY IS THE BEST? "ACCUMULATED WISDOM" INEFFICIENT AND SLOW

CHANGE OF PHILOSOPHY  $\Rightarrow$  DETERMINISTIC MINIMIZATION (GRADIENT DESCENT) GO FOR THE ABSOLUTE MINIMUM, AND (HYPER)OPTIMIZE



- PYTHON-BASED KERAS + TENSORFLOW FRAMEWORK
- EACH BLOCK INDEPENDENT LAYER
- CAN VARY ALL ASPECTS OF METHODOLOGY

### FITTING THE METHODOLOGY HYPEROPTIMIZATION SCANS



Neural Network	
NEURAL NEIWORK	
NT (ψ)	
Number of Layers (*)	
TIONIBBIL OF BILLDING ()	

SIZE OF EACH LAYER
DROPOUT
ACTIVATION FUNCTIONS (\*)
INITIALIZATION FUNCTIONS (\*)

FIT OPTIONS

OPTIMIZER (\*)

INITIAL LEARNING RATE (\*)

MAXIMUM NUMBER OF EPOCHS (\*) STOPPING PATIENCE (\*)

POSITIVITY MULTIPLIER (\*)

• SCAN PARAMETER SPACE

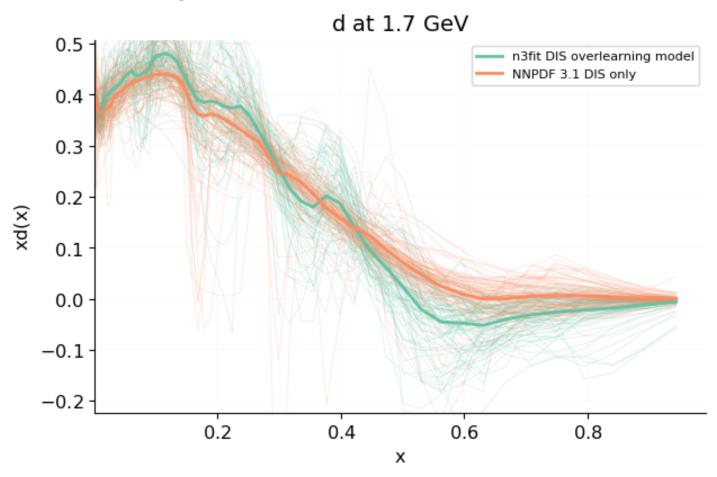
ullet OPTIMIZE FIGURE OF MERIT: VALIDATION  $\chi^2$ 

BAYESIAN UPDATING

#### FITTING THE METHODOLOGY

THE OVERFITTING PROBLEM

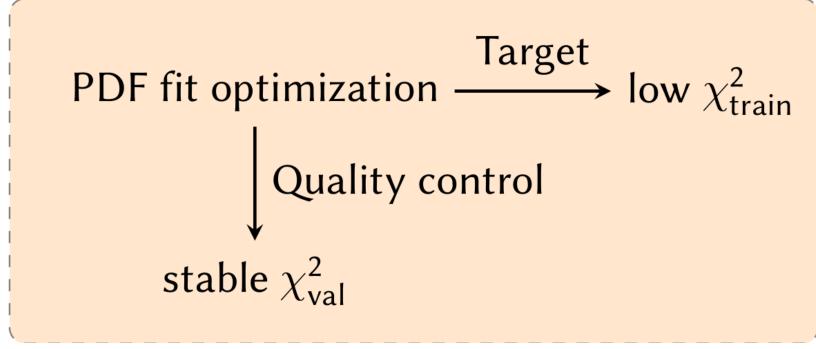
DOWN QUARK: HYPEROPTIMIZED VS. STANDARD



- NNPDF3.1: WIGGLES: FINITE SIZE  $\Rightarrow$  WILL GO AWAY AS  $N_{\text{rep}}$  GROWS
- N3FIT: WIGGLY PDFS  $\Leftrightarrow$  OVERFITTING  $\Rightarrow$  WILL NOT GO AWAY ( $\chi^2_{\rm train} \ll \chi^2_{\rm valid}$ !!)

#### WHAT HAPPENED?

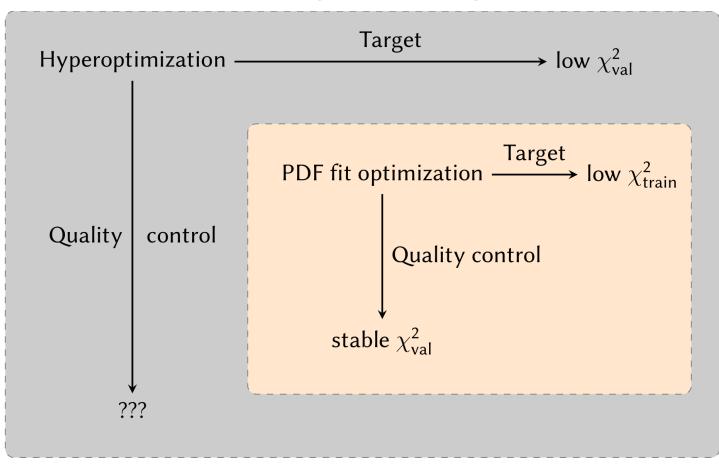
#### **OPTIMIZATION**



CROSS-VALIDATION SELECTS THE OPTIMAL MINIMUM

#### WHAT HAPPENED?

#### **HYPEROPTIMIZATION**



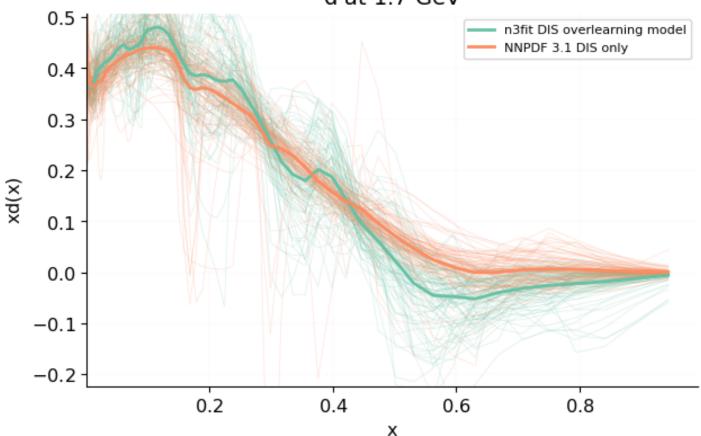
WE ARE MISSING A SELECTION CRITERION

#### FITTING THE METHODOLOGY

#### THE OVERFITTING PROBLEM

DOWN QUARK: HYPEROPTIMIZED VS. STANDARD

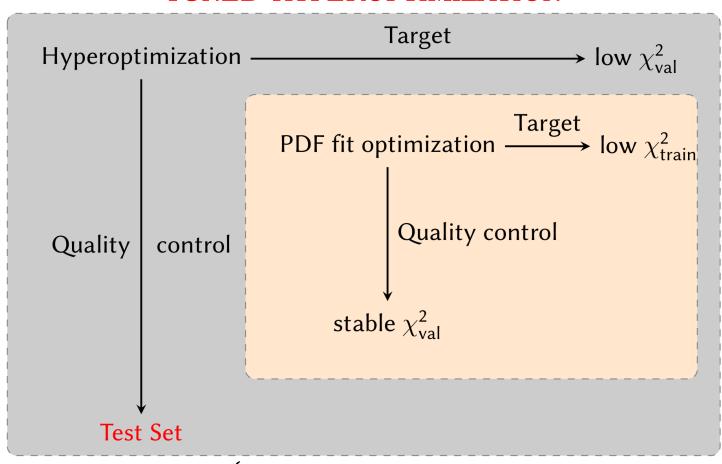




- NNPDF3.1: WIGGLES: FINITE SIZE  $\Rightarrow$  WILL GO AWAY AS  $N_{\rm rep}$  GROWS
- N3FIT: WIGGLY PDFS  $\Leftrightarrow$  OVERFITTING  $\Rightarrow$  WILL NOT GO AWAY ( $\chi^2_{\rm train} \ll \chi^2_{\rm valid}$ !!)
- CORRELATIONS BETWEEN TRAINING AND VALIDATION DATA

#### MACHINE LEARNING THE SOLUTION

#### TUNED HYPEROPTIMIZATION

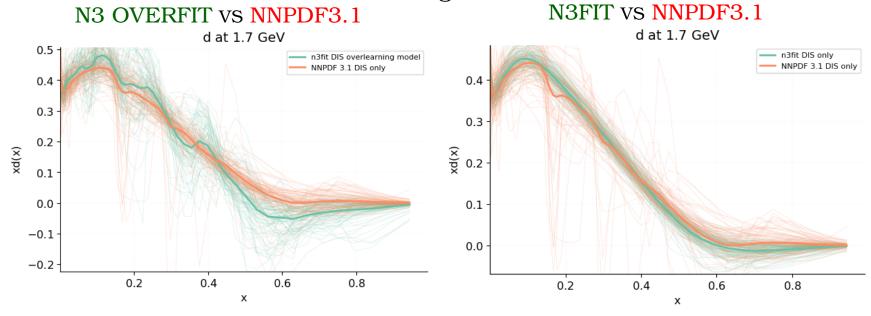


COMPARE TO A A TEST SET (NEW SET OF DATA PREVIOUSLY NOT USED AT AL)
TESTS GENERALIZATION POWER

#### THE TEST SET METHOD

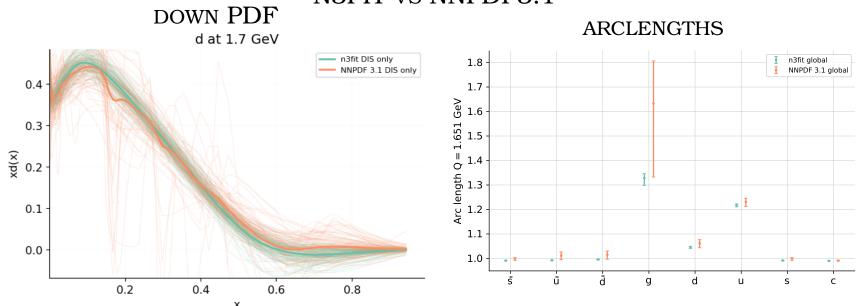
- COMPLETELY UNCORRELATED TEST SET
- OPTIMIZE ON WEIGHTED AVERAGE OF VALIDATION AND TEST  $\Rightarrow$  NO OVERLEARNING

#### HYPEROPTIMIZED PDFS DOWN QUARK



#### THE TEST SET METHOD

N3FIT vs NNPDF3.1

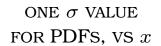


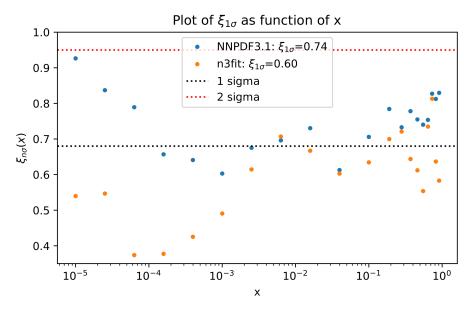
- NO OVERFITTING
- COMPARED TO NNPDF3.1
  - MUCH Greater Stability  $\Rightarrow$  Fewer Replicas for Equal accuracy
  - UNCERTAINTIES SOMEWHAT REDUCED

#### **CLOSURE TESTS AGAIN**

ONE  $\sigma$ : ACTUAL/PREDICTED FOR DATA, BY EXPERIMENT

	NNPDF3.1 ratio	n3fit ratio
experiment		
NMC	0.882828	0.843427
$\operatorname{SLAC}$	0.767063	0.690118
BCDMS	0.730569	0.770704
CHORUS	0.698907	0.734656
NTVDMN	0.991090	0.797017
HERACOMB	0.847359	1.326333
HERAF2CHARM	1.867597	3.566076
F2BOTTOM	1.124157	1.532634
DYE886	0.655955	0.857915
DYE605	0.585725	0.870151
CDF	0.961652	0.779424
D0	0.881199	1.015202
ATLAS	0.904127	1.132229
CMS	1.090241	1.017136
LHCb	1.092194	0.993525
Total	0.842168	0.940737





- UNCERTAINTIES WELL ESTIMATED ON AVERAGE; BUT SIZABLE FLUCTUATIONS
- ONE  $\sigma$  PERFECT IN DATA REGION; BUT UNDERESTIMATED IN EXTRAPOLATION

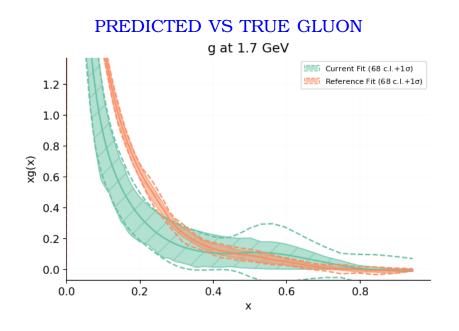
#### THE "FUTURE TEST"

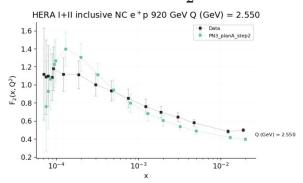
COULD WE "PREDICT" THE RISE OF  $F_2$  AT HERA?

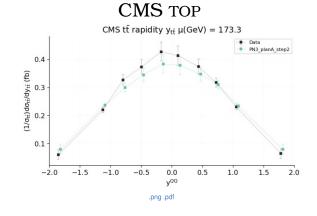
ONLY PRE-HERA DATA USED

PREDICTION COMPARED TO DATA

HERA  $F_2$ 







- N3FIT METHOLOGY APPLIED AND HYPEROPTIMIZED TO PRE-HERA DATASET
- RESULTS WITH PDF UNCERTAINTY COMPARED TO FUTURE DATA
- $\chi^2/{\rm dat}$ =1.1 On full predicted current dataset (about 200 datapoints)

**SUCCESS!** 

## REMOVING BIAS

# ANY BIAS LEFT? OPEN PROBLEMS

- IN N3FIT, WHO PICKS THE TEST SET?
- IN FUTURE TEST, EXTRAPOLATION BASED ON NNPDF PREPROCESSING METHODOLOGY

$$F(x) = x^{\alpha} (1 - x)^{\beta} NN(x),$$

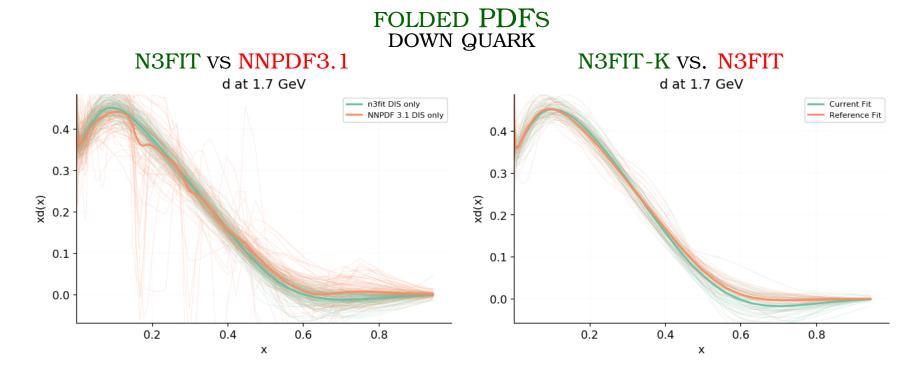
 $\alpha$ ,  $\beta$  RANDOMLY VARIED WITH UNIFORM DISTRIBUTION IN

SELF-CONSISTENTLY DETERMINED RANGE

• WHAT ABOUT MISSING HIGHER ORDER CORRECTIONS?

# AUTOMATIC GENERALIZATION K-FOLDINGS THE BASIC IDEA:

- DIVIDE THE DATA INTO n REPRESENTATIVE SUBSETS EACH CONTAINING PROCESS TYPES, KINEMATIC RANGE OF FULL SET
- FIT n-1 SETS AND USE n-TH SET AS TEST  $\Rightarrow n$  VALUES OF  $\chi^2_{\rm test,\ i}$
- HYPEROPTIMIZE ON MEAN AND STANDARD DEVIATION OF  $\chi^2_{\rm test,\ i}$   $\to$  GOOD & STABLE GENERALIZATION



#### THE INTERPOLATION/EXTRAPOLATION PROBLEM PREPROCESSING AND SMALL/LARGE x BEHAVIOUR

- NEURAL NETS ARE "PREPROCESSED":  $f(x) = x^{\alpha}(1-x)^{\beta}NN(x)$
- EXPONENTS RANDOMLY VARIED IN RANGE REPLICA BY REPLICA
- RANGE OF PREPROCESSING EXPONENTS SELF-CONSISTENTLY DETERMINED



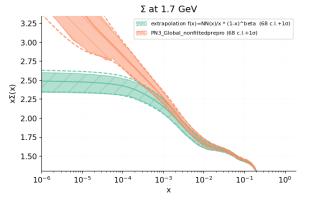
- FIT "SATURATES" ⇒ PREPROCESSING REPRODUCED X
- IF PREPROCESSING REMOVED, ALL PDFS HAVE THE SAME BEHAVIOUR

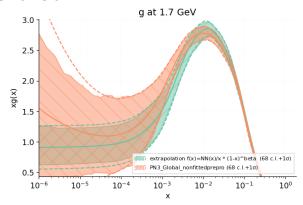
#### GLUON PREPROCESSING

#### Gluon alpha effective exponent

#### 2.2 170120-007, 68% c.l. 170120-007, 2x68% c.l. 161208-ir-003, 68% c.l. 161208-jr-003, 2x68% c.l. 1.6 1.4 0.6 0.2 10<sup>-6</sup>

#### PREPROCESSING VS NO PREPROCESSING: SINGLET & GLUON





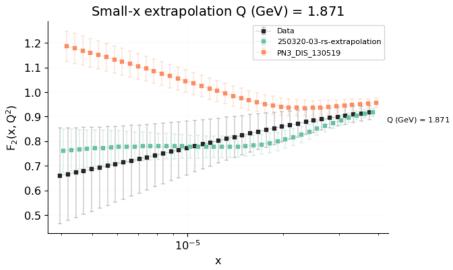
## PREPROCESSING AND SMALL/LARGE *x* BEHAVIOUR TOWARDS A SOLUTION: THE GAUSSIAN PROCESS

- DETERMINE CORRELATION LENGTH BETWEEN POINTS USING A KERNEL
- PROPAGATE A PRIOR GAUSSIAN INTO EXTRAPOLATION
- GENERATE GAUSSIAN PSEUDODATA TO BE ADDED TO FIT

#### **PSEUDODATA**

# 1.0 0.8 0.6 0.0 0.0 Prediction Experiment Pseudodata 95% confidence interval 68% confidence interval 68% confidence interval

#### FIT TO PSEUDODATA VS STANDARD

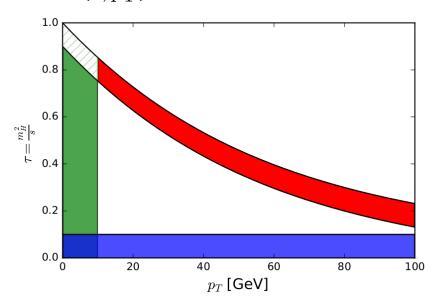


- NO PREPROCESSING NEEDED
- $\ln x$ , x INPUT REPLACED BY SCALED INPUT

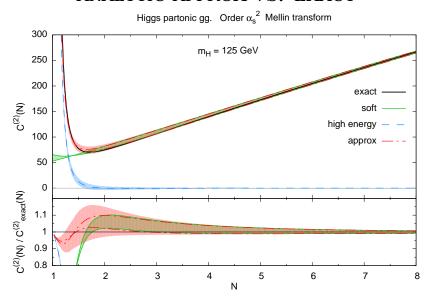
## THEORY UNCERTAINTIES MISSING HIGHER ORDERS FROM ASYMPTOTICS

- HIGHER ORDERS KNOWN IN VARIOUS KINEMATIC LIMITS FROM RESUMMATION
- $\bullet$  used in the past to construct analytic approximation to full MHO: e.g. Higgs in gluon fusion at  $N^3LO$
- MACHINE LEARNING MHO?

#### $(\tau, p_T)$ RESUMMATION REGIONS



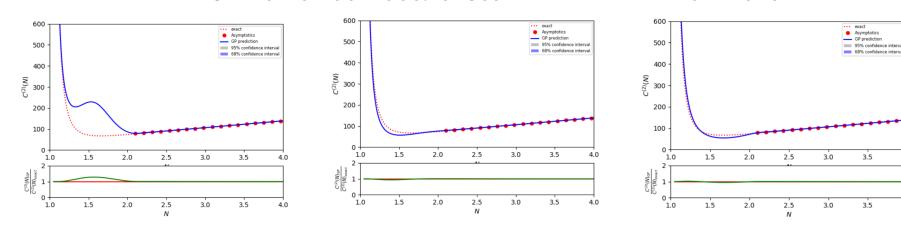
#### NNLO N-SPACE GGHIGGS ANALYTIC APPROX VS. EXACT



## THEORY UNCERTAINTIES NAIVE IDEA: GAUSSIAN PROCESS AGAIN

- PROPAGATE ASYPTOTICS INTO "CENTRAL" REGION USING GAUSSIAN PROCESS
- HYPEROPTIMIZE KERNEL CHOICE AND PARAMETERS BASED ON KNOWN CASES

#### NNLO N-SPACE GGHIGGS: GAUSSIAN KERNEL INTERPOLATIONS



• TOO FEW DATA  $\Rightarrow$  RESULTS UNSTABLE, DEPEND ON CHOICE OF KERNEL

# THEORY UNCERTAINTIES TRANSFER LEARNING?

THE BASIC IDEA:

- PERTURBATIVE DEPENDENCE KNOWN UP TO NNLO FOR MANY PROCESSES
- LEARN PERTURBATIVE DEPENDENCE FROM KNOWN CASES
- ADD FINAL LAYER WHICH EXTRAPOLATES FROM ASYMPTOTICS

....STAY TUNED!

## THE WORK OF MANY PEOPLE THE N3PDF TEAM



Milan, December 2019