

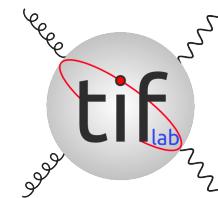


PARTON DISTRIBUTIONS AND MACHINE LEARNING FROM THE LHC TO THE EIC

STEFANO FORTE
UNIVERSITÀ DI MILANO & INFN



UNIVERSITÀ DEGLI STUDI DI MILANO
DIPARTIMENTO DI FISICA



Istituto Nazionale di Fisica Nucleare

SUMMARY

- **LIFE BEFORE THE LHC**
 - PARTON DISTRIBUTIONS AND THEIR DETERMINATION
 - THE PROBLEM OF PDF UNCERTAINTIES
- **THE PROBLEM OF PDF UNCERTAINTIES**
 - TOLERANCE
 - GENERALIZATION
- **PDFs AS AN AI PROBLEM**
 - THE NEURAL MONTECARLO
 - NEURAL NETWORK ARCHITECTURE AND TRAINING
- **FROM AI TO MACHINE LEARNING**
 - OPTIMIZATION AND HYPEROPTIMIZATION
 - THE MEANING OF CORRELATIONS
- **VALIDATION**
 - CLOSURE TESTS AND FUTURE TESTS
 - THE MEANING OF UNCERTAINTIES
- **THE STATE OF THE ART**
 - DATA AND UNCERTAINTIES
 - THEORETICAL ACCURACY AND INTRINSIC CHARM
- **UNDERSTANDING MACHINE LEARNING**
 - DISTRIBUTIONS IN FUNCTION SPACE AND IN FEATURE SPACE
 - GENERALIZATION
- **THE IMPACT OF THE EIC**
 - FROM QCD TO NEW PHYSICS
 - THE EIC AND MACHINE LEARNING

PDFS IN HISTORY

PDFs: THE EARLY DAYS

THE DISCOVERY OF THE W (1984)

THEORETICAL PREDICTION

42

G. Altarelli et al. / Vector boson production

TABLE 2

Values (in nb) of the total cross sections for W^\pm and Z^0 production

\sqrt{s} (GeV)	$W^+ + W^-$	$W^+ + W^-$	$W^+ + W^-$	Z^0	Z^0	Z^0	$\frac{\sigma(W^+ + W^-)}{\sigma(Z^0)}$	$\frac{\sigma(W^+ + W^-)}{\sigma(Z^0)}$	$\frac{\sigma(W^+ + W^-)}{\sigma(Z^0)}$
	GHR	DO1	DO2	GHR	DO1	DO2	GHR	DO1	DO2
540	4.2	4.3	4.1	1.3	1.3	1.2	3.1	3.4	3.5
700	6.2	6.3	6.1	2.0	1.9	1.8	3.1	3.3	3.4
1000	9.5	9.5	9.6	3.1	3.0	2.9	3.1	3.2	3.3
1300	12.5	12.5	12.9	4.0	3.9	3.9	3.1	3.2	3.3
1600	15.5	15.6	16.5	5.0	4.8	5.0	3.1	3.2	3.3

ALTARELLI, ELLIS, GRECO, MARTINELLI, 1984

EXPERIMENTAL DISCOVERY



EUROPEAN ORGANIZATION FOR NUCLEAR RESEARCH

CERN-EP/85-108
11 July 1985

W PRODUCTION PROPERTIES AT THE CERN SPS COLLIDER

UA1 Collaboration, CERN, Geneva, Switzerland

Aachen¹–Amsterdam (NIKHEF)²–Annecy (LAPP)³–Birmingham⁴–CERN⁵–
Harvard⁶–Helsinki⁷–Kiel⁸–London (Imperial College⁹ and Queen Mary College¹⁰)–Padua¹¹–
Paris (Coll. de France)¹²–Riverside¹³–Rome¹⁴–Rutherford Appleton Lab.¹⁵–
Saclay (CEN)¹⁶–Victoria¹⁷–Vienna¹⁸–Wisconsin¹⁹ Collaboration

The corresponding experimental result for the 1984 data at $\sqrt{s} = 630$ GeV is

$$(\sigma \cdot B)_W = 0.63 \pm 0.05 (\pm 0.09) \text{ nb.}$$

This is in agreement with the theoretical expectation [14] of $0.47^{+0.14}_{-0.08}$ nb. We note that the 15%

- AGREEMENT AND UNCERTAINTIES AT 20% CONSIDERED TO BE SATISFACTORY
- RESULTS FROM DIFFERENT PDF SETS DIFFER BY AT LEAST 5%
- NO WAY TO ESTIMATE PDF UNCERTAINTIES

PDFs: THE EARLY DAYS

THE DISCOVERY OF THE W (1984)

PDFs IN 1984

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	GHR	DO1	DO2	GHR	DO1	DO2	GHR	DO1	DO2	GHR	DO1	DO2
540	4.2	4.3	4.1	1.3	1.3	1.2	3.1	3.4	3.5			
700	6.2	6.3	6.1	2.0	1.9	1.8	3.1	3.3	3.4			
1000	9.5	9.5	9.6	3.1	3.0	2.9	3.1	3.2	3.3			
1300	12.5	12.5	12.9	4.0	3.9	3.9	3.1	3.2	3.3			
1600	15.5	15.6	16.5	5.0	4.8	5.0	3.1	3.2	3.3			

ALTARELLI, ELLIS, GRECO, MARTINELLI, 1984

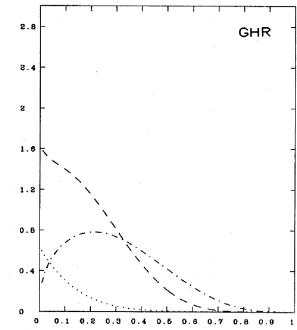


FIG. 25. Parton distributions of Glück, Hoffmann, and Reya (1982), at $Q^2=5$ GeV^2 : valence quark distribution $x[u_v(x) + d_v(x)]$ (dotted-dashed line), $xG(x)$ (dashed line), and $q_v(x)$ (dotted line).

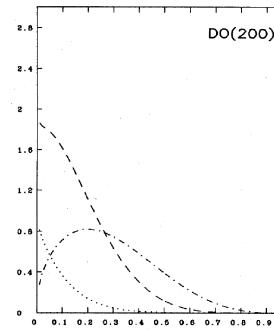


FIG. 27. "Soft-gluon" ($\Lambda=200$ MeV) parton distributions of Duke and Owens (1984) at $Q^2=5$ GeV^2 : valence quark distribution $x[u_v(x) + d_v(x)]$ (dotted-dashed line), $xG(x)$ (dashed line), and $q_v(x)$ (dotted line).

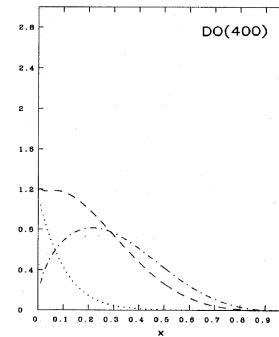


FIG. 26. "Hard-gluon" ($\Lambda=400$ MeV) parton distributions of Duke and Owens (1984) at $Q^2=5$ GeV^2 : valence quark distribution $x[u_v(x) + d_v(x)]$ (dotted-dashed line), $xG(x)$ (dashed line), and $q_v(x)$ (dotted line).

Rev. Mod. Phys., Vol. 56, No. 4, October 1984

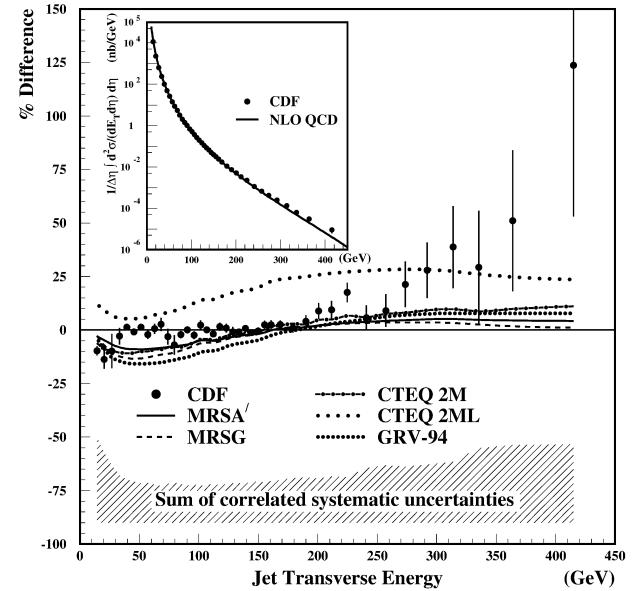
GHR VS DUKE-OWENS

- AGREEMENT AND UNCERTAINTIES AT 20% CONSIDERED TO BE SATISFACTORY
- RESULTS FROM DIFFERENT PDF SETS DIFFER BY AT LEAST 5%
- NO WAY TO ESTIMATE PDF UNCERTAINTIES

PDFS AND DISCOVERY

THE DISCOVERY OF QUARK COMPOSITENESS? (1995)

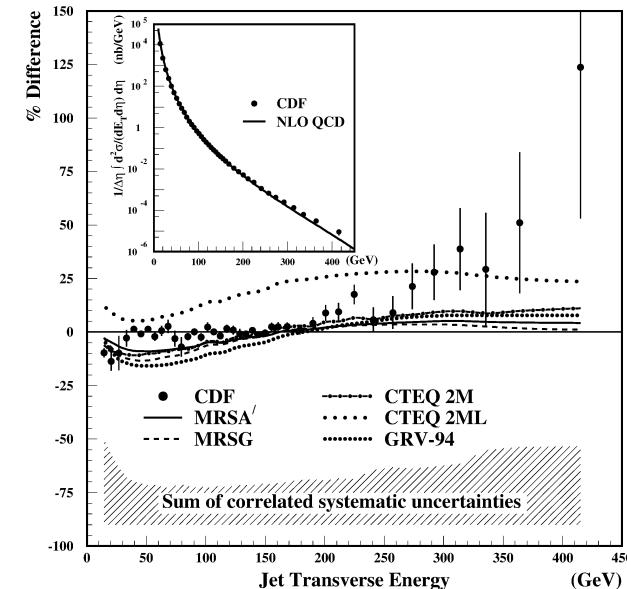
- DISCREPANCY BETWEEN QCD CALCULATION AND CDF JET DATA (1995)
- EVIDENCE FOR QUARK COMPOSITENESS
- .



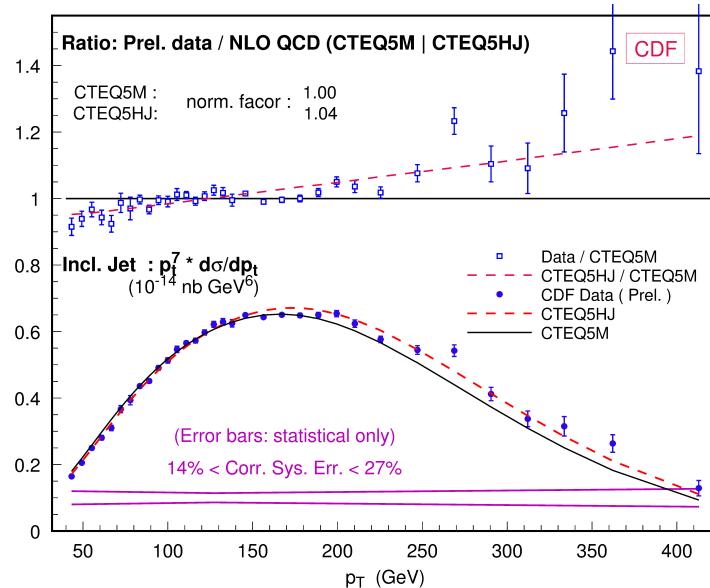
PDFS AND DISCOVERY

THE DISCOVERY OF THE GLUON (1995)

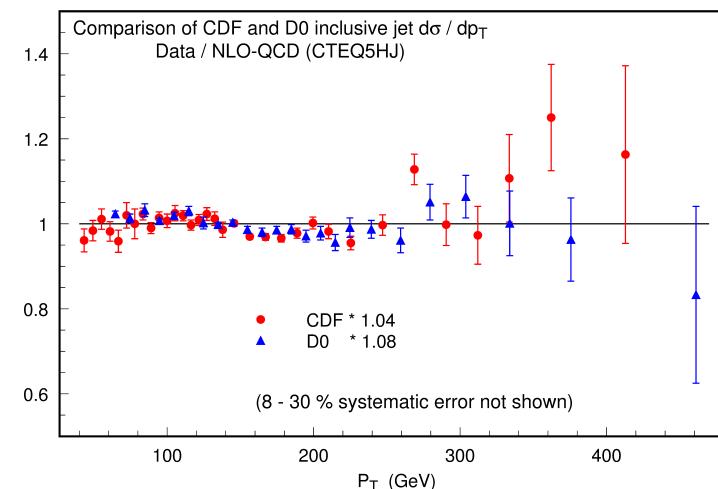
- DISCREPANCY BETWEEN QCD CALCULATION AND CDF JET DATA (1995)
- ~~EVIDENCE FOR QUARK COMPOSITENESS~~
- NO INFO ON PARTON UNCERTAINTY \Rightarrow
RESULT STRONGLY DEPENDS ON
GLUON AT $x \gtrsim 0.1$



**DISCREPANCY REMOVED IF JET DATA INCLUDED IN THE FIT
NEW CTEQ FIT (1996)**

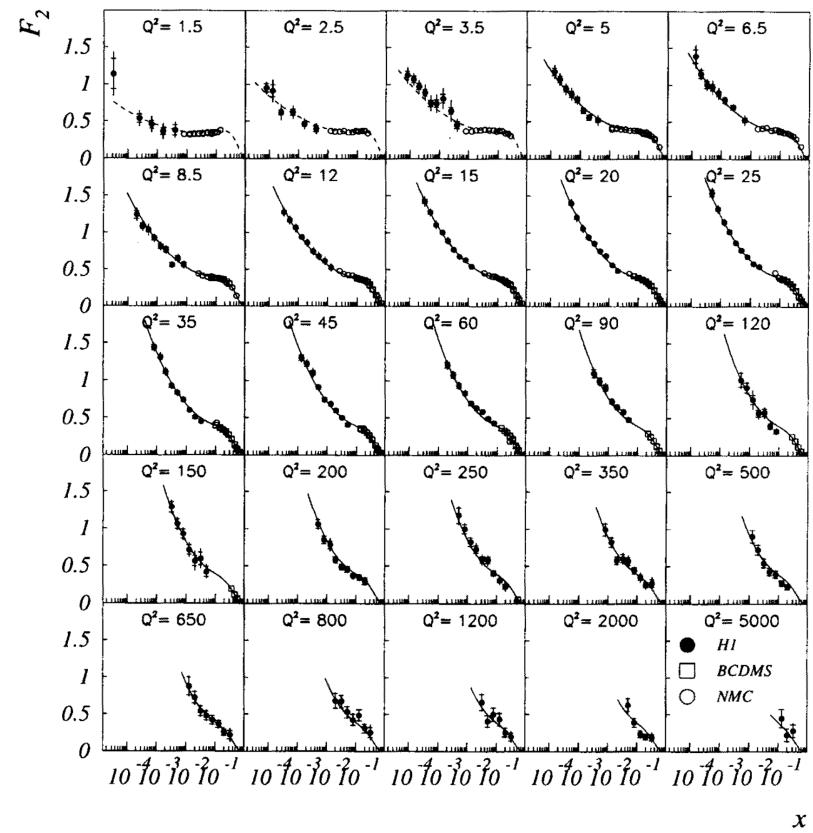
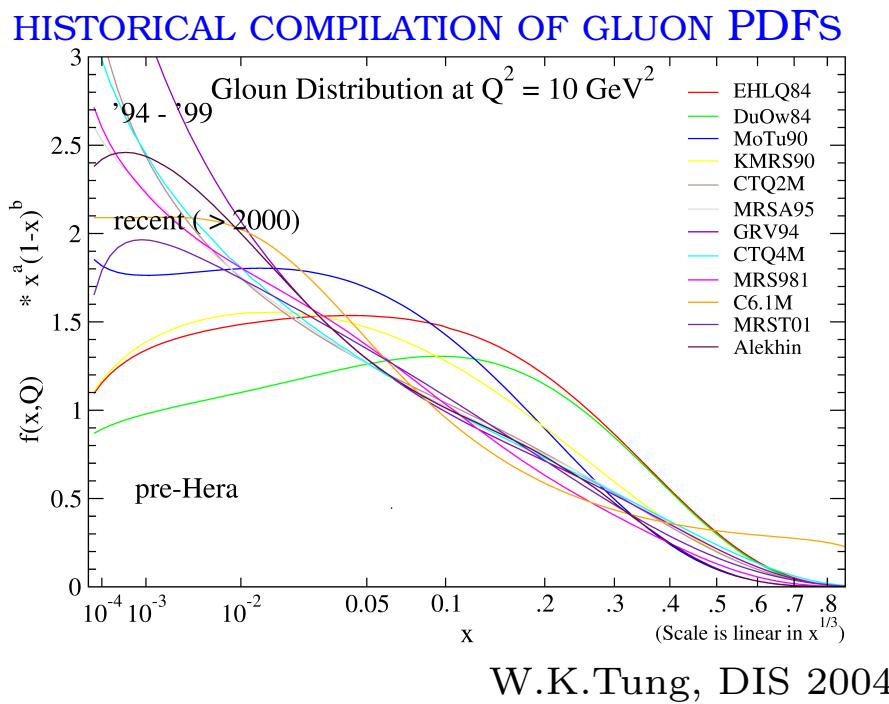


FINAL CTEQ FIT (1998)



PDFS AND DISCOVERY

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



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

DISCOVERING PDFs WHAT'S THE PROBLEM?

D. Kosower, 1999

- FOR A SINGLE QUANTITY, WE QUOTE 1 SIGMA ERRORS: $\text{VALUE} \pm \text{ERROR}$
- FOR A PAIR OF NUMBERS, WE QUOTE A 1 SIGMA ELLIPSE
- FOR A FUNCTION, WE NEED AN “ERROR BAR” IN A SPACE OF FUNCTIONS

MUST DETERMINE A PROBABILITY DENSITY (MEASURE) IN THE SPACE OF FUNCTIONS

⇒ MUST DETERMINE AN INFINITE-DIMENSIONAL OBJECT
FROM A FINITE SET OF DATA POINTS

A SOLUTION? ~ 2000

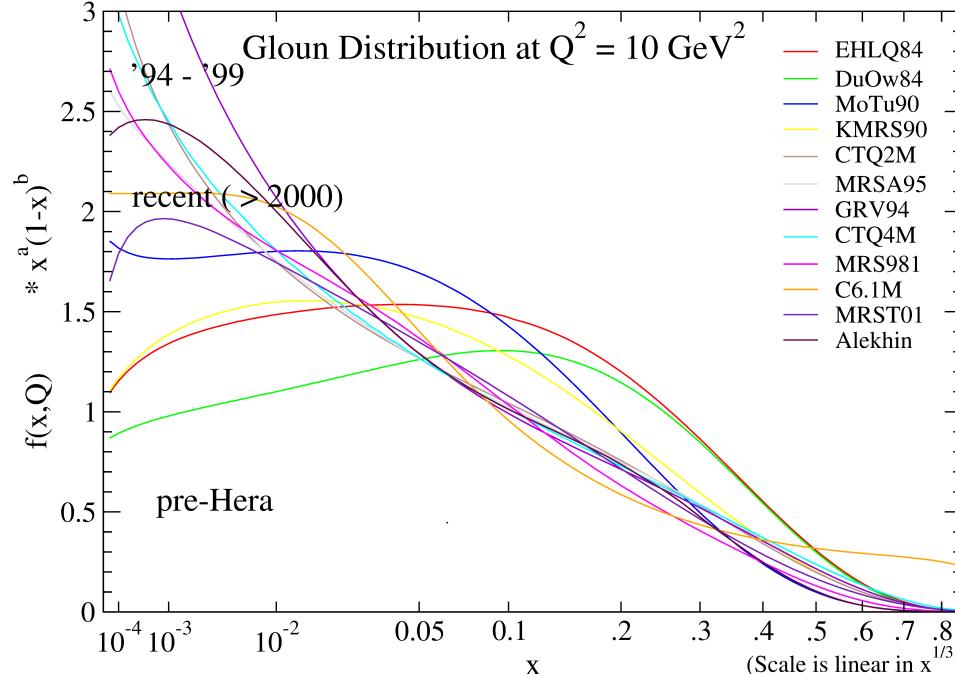
- FIT A MODEL-INSPIRED FUNCTIONAL FORM
- DETERMINE UNCERTAINTY BY STANDARD ERROR PROPAGATION
 $\Rightarrow \Delta\chi^2 = 1$ CONTOUR IN PARAMETER SPACE

gluon parametrization (MRST 2004)

$$xg(x, Q_0^2) = A_g(1-x)^{\eta_g}(1 + \epsilon_g x^{0.5} + \gamma_g x)x^{\delta_g} - A_{-}(1-x)^{\eta_{-}}x^{-\delta_{-}}$$

- PROBLEM REDUCED TO FINITE-DIMENSIONAL
- WHO PICKS THE FUNCTIONAL FORM?

HISTORICAL COMPILED OF GLUON PDFS

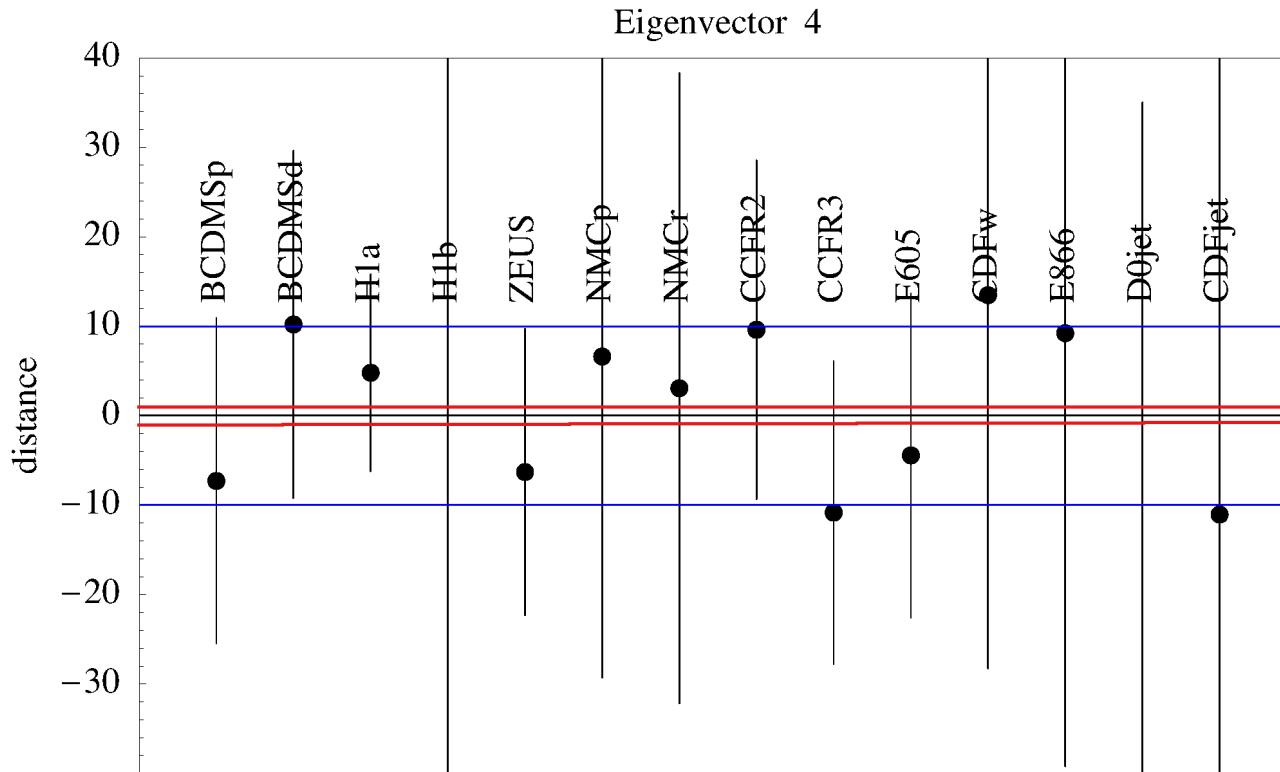


PDF UNCERTAINTIES

FIRST PDFS WITH UNCERTAINTIES (2002) “TOLERANCE”

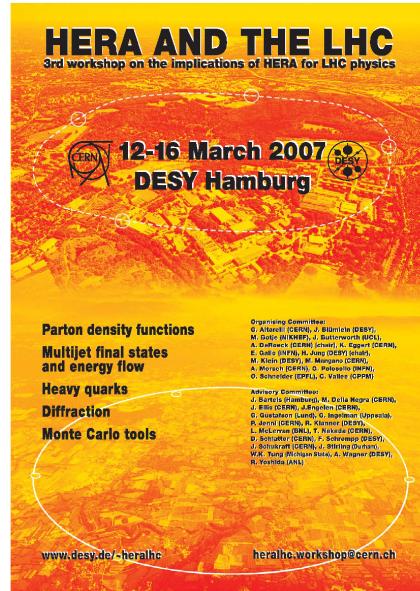
one sigma & ten sigma intervals for typical
covariance matrix eigenvalue

vs best value and uncertainty from individual experiments



- SPREAD OF BEST-FIT FROM DIFFERENT DATA **HUGE**
W.R. TO $\Delta\chi^2 = 1$ **ERROR PROPAGATION FORMULA**
- PDF **UNCERTAINTIES RESCALED** BY “TOLERANCE” $T \sim 10$

THE HERA-LHC WORKSHOPS



HERA and the LHC
A workshop on the implications of
HERA for LHC physics

CERN - DESY Workshop
26 - 30 May 2008

CERN

latest update January 19, 2008
[Download Workshop poster](#)

[HERA - LHC workshop 2004 – 2005](#)
[HERA - LHC workshop 2006](#)
[HERA - LHC workshop 2007](#)
[HERA – LHC working group week Oct 2007](#)

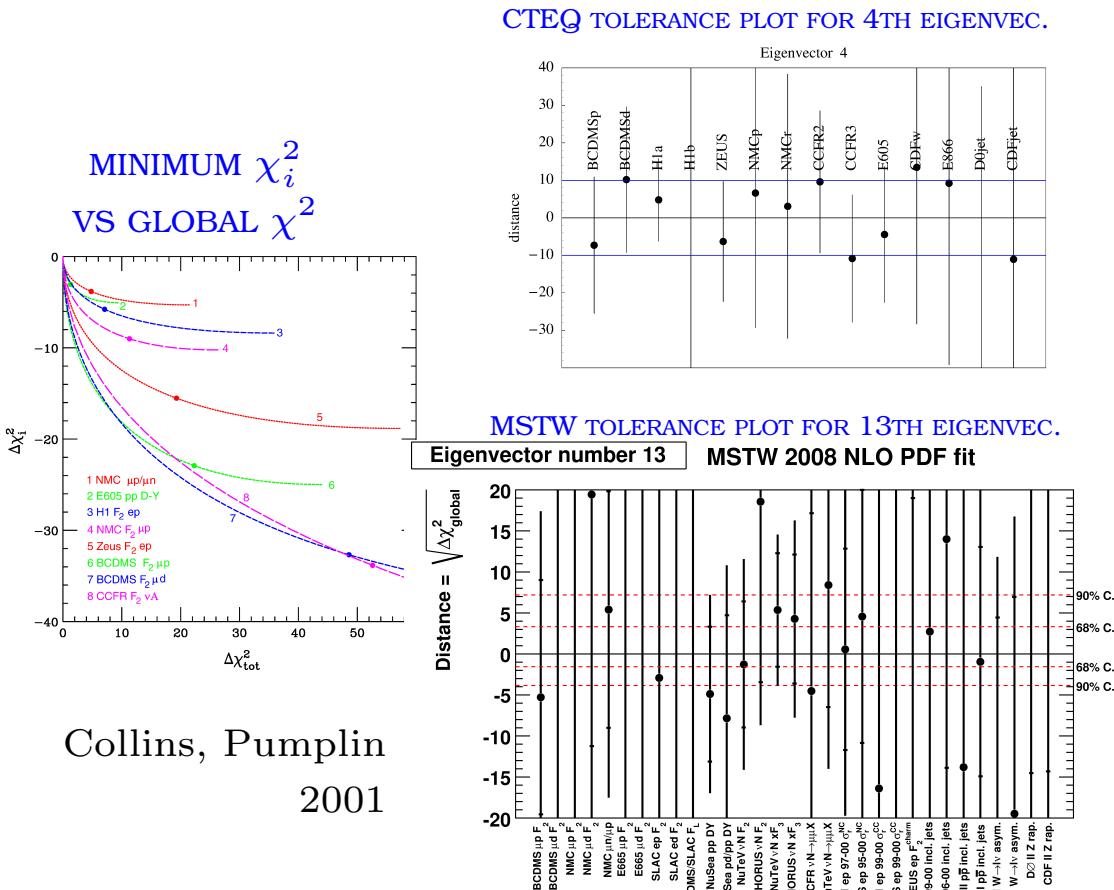
Please register here
List of Participants

HERALHC: 2004-2008
PDF4LHC: 2008-

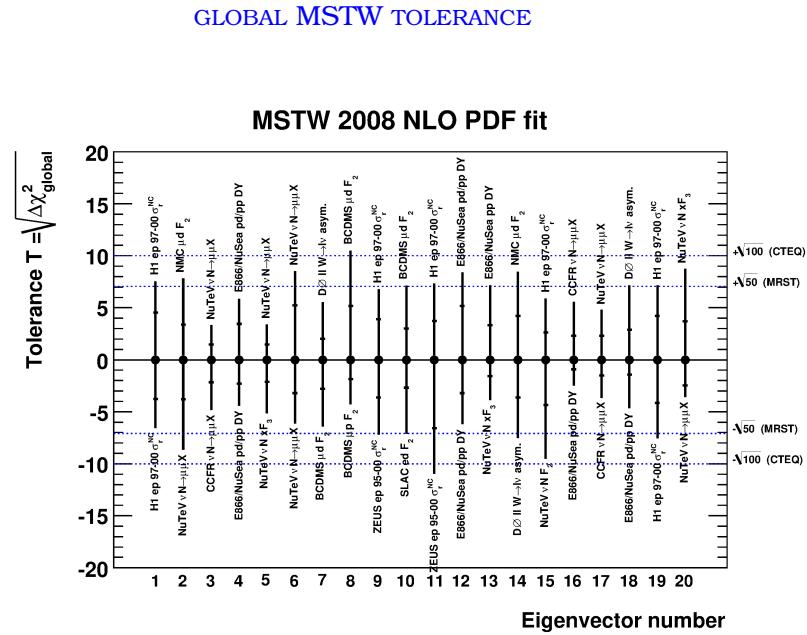
RELIABLE PDF UNCERTAINTY ESTIMATES? DYNAMICAL TOLERANCE

“estimates of PDF uncertainties follow an ad-hoc recipe defined by the fitters” (C. Hays, 09)

- **TOLERANCE** \Rightarrow ENVELOPE OF UNCERTAINTIES OF EXPERIMENTS
- **DYNAMICAL** \Rightarrow SEPARATELY DETERMINED FOR EACH HESSIAN EIGENVECTOR



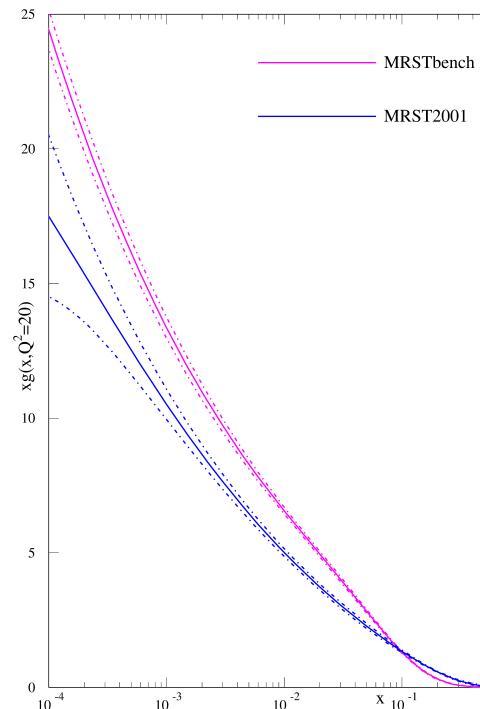
Collins, Pumplin
2001



THE HERA-LHC BENCHMARK PROBLEM (2005)

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

BENCHMARK VS DEFAULT GLUON



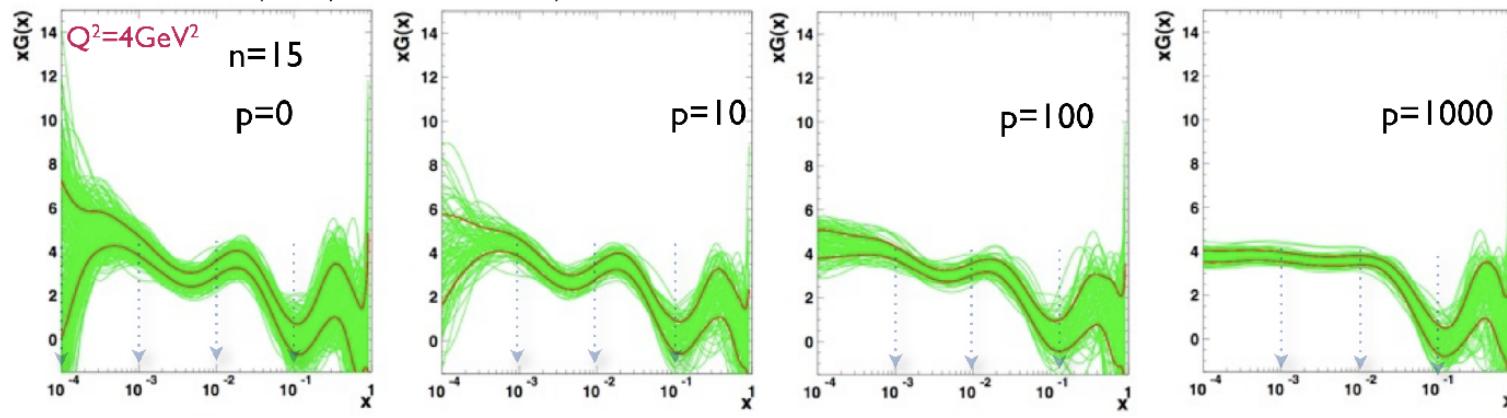
“...the partons extracted using a very limited data set are completely incompatible, even allowing for the uncertainties, with those obtained from a global fit with an identical treatment of errors...The comparison illustrates the problems in determining the true uncertainty on parton distributions.”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

ATTEMPTS AT A SOLUTION

(Glazov, Radeșcu, 2009)

CHEBYSHEV AND LENGTH PENALTY

- OLD IDEA (PARISI, SOURLAS, 1978):
EXPAND PDFS OVER BASIS OF ORTHOGONAL POLYNOMIALS
- LENGTH PENALTY STABILIZATION:
CONTRIBUTION TO χ^2 PROPORTIONAL TO THE ARCLENGTH WITH WEIGHT p
- RESULTS STRONGLY DEPENDENT ON ARBITRARY CHOICE OF p



PDFS AT THE DAWN OF THE LHC

CAN ONE CALCULATE

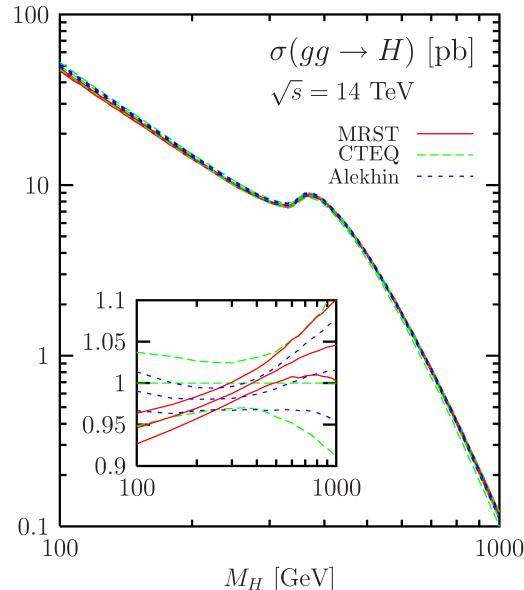
THE HIGGS CROSS SECTION???

AT LHC START

PROGRESS

gluon luminosities

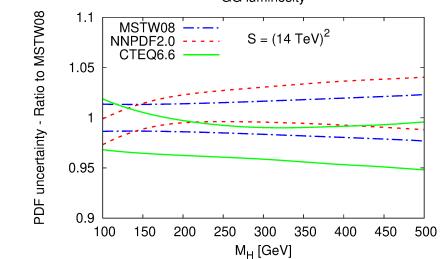
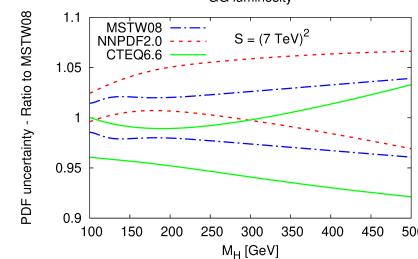
BEFORE HERALHC
OLD DISAGREEMENTS



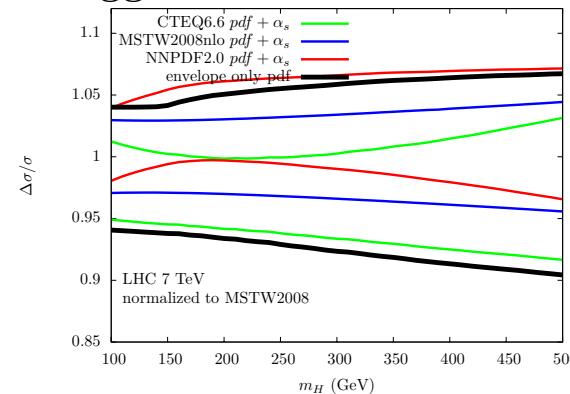
(Djouadi, Ferrag, 2004)

CTEQ, MRST (global); Alekhin (DIS)

- WIDELY DIFFERENT UNCERTAINTIES
- POOR AGREEMENT WITHIN UNCERTAINTIES
- TOLERANCE? $\Delta\chi^2 = 100$ (CTEQ); 50 (MRST); 1 (ALEKHIN)



gg → H cross section



(Demartin et al., 2010)

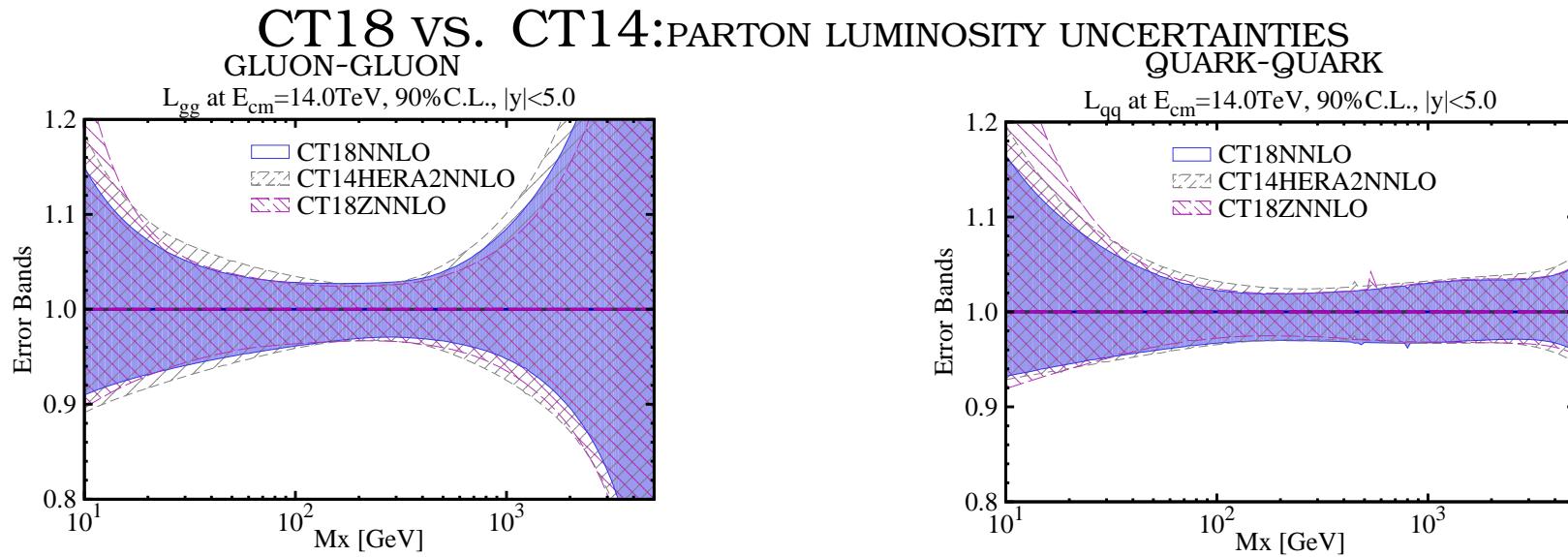
- THREE GLOBAL (DIS+HADRONIC) PDF SETS AVAILABLE
- REASONABLE AGREEMENT OF CENTRAL VALUES & UNCERTAINTIES

THE MODEL-DEPENDENT APPROACH: PROGRESS

- INCREASINGLY COMPLEX PARAMETRIZATION
- UNDERLYING PHYSICALLY MOTIVATED ANSATZ (SINCE 1973!) $f_i(x, Q_0^2) = x^\alpha(1-x)^\beta g_i(x)$; $g_i(x)$ POLYNOMIAL IN x OR \sqrt{x}
- Example: MMHT 2015:
 - basis functions g ; $u_v = u - \bar{u}$; $d_v = d - \bar{d}$; $S = 2(\bar{u} + \bar{d}) + s + \bar{s}$; $s_+ = s + \bar{s}$; $\Delta = \bar{d} - \bar{u}$; $s_- = s - \bar{s}$.
 - for all but Δ s_- , $g \Rightarrow xf_i(x, Q_0^2) = Ax^\alpha(1-x)^\beta \left(1 + \sum_{i=1}^4 a_i T_i(y(x))\right)$; T_i Chebyshev polynomials, $y = 1 - 2\sqrt{x} \leftrightarrow$ must map $x = [0, 1]$ into $y = [-1, 1]$; $T_i(-1) = T_i(1) = 1$
 - gluon $xg(x, Q_0^2) = Ax^\alpha(1-x)^\beta \left(1 + \sum_{i=1}^2 a_i T_i(y(x))\right) + A'xT\alpha'(1-x)^{\beta'}$
 - sea asymmetry $x\Delta(x, Q_0^2) = Ax^\alpha(1-x)^\beta(1 + \gamma x + \epsilon x^2)$
 - strangeness asymmetry $x\Delta(x, Q_0^2) = Ax^\alpha(1-x)^\beta(1 - x/x_0)$
 - 41 parameters, 4 fixed by sum rules
 - 12 parms fixed at best fit, remaining 25 used for (hessian) covariance matrix

THE MODEL-DEPENDENT APPROACH: PROBLEMS ADDING NEW DATA PARTON PARAMETRIZATIONS

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

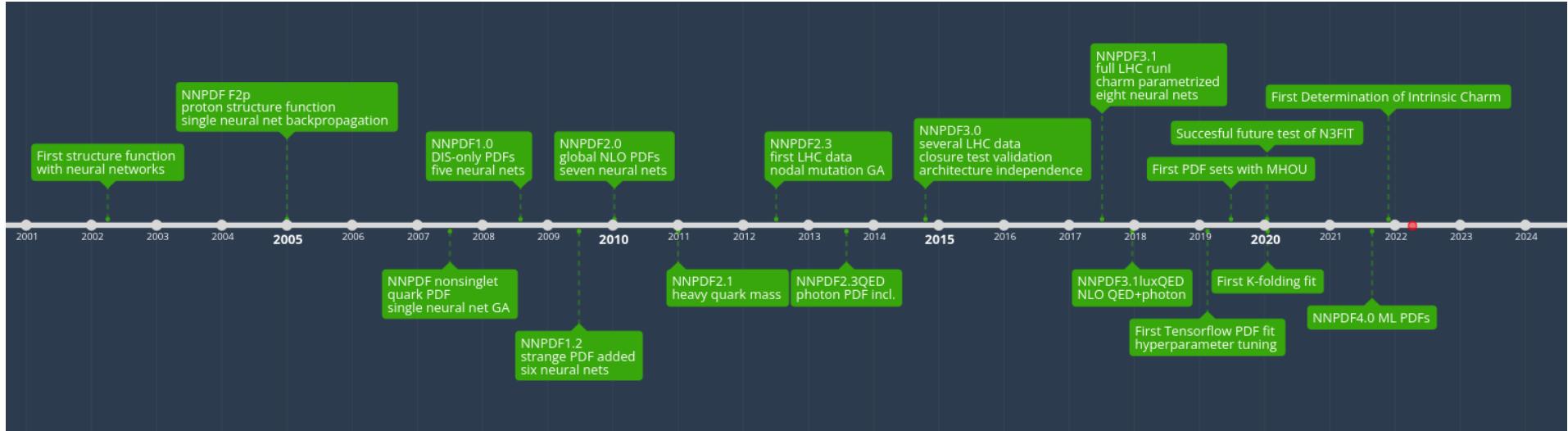


**MORE DATA \Rightarrow BIGGER UNCERTAINTIES (?)
BIAS?**

PDFS AND AI

PROTON STRUCTURE AS AN AI PROBLEM: NNPDF

UNBIASED MODELING WITH UNCERTAINTIES IN A SPACE OF FUNCTIONS

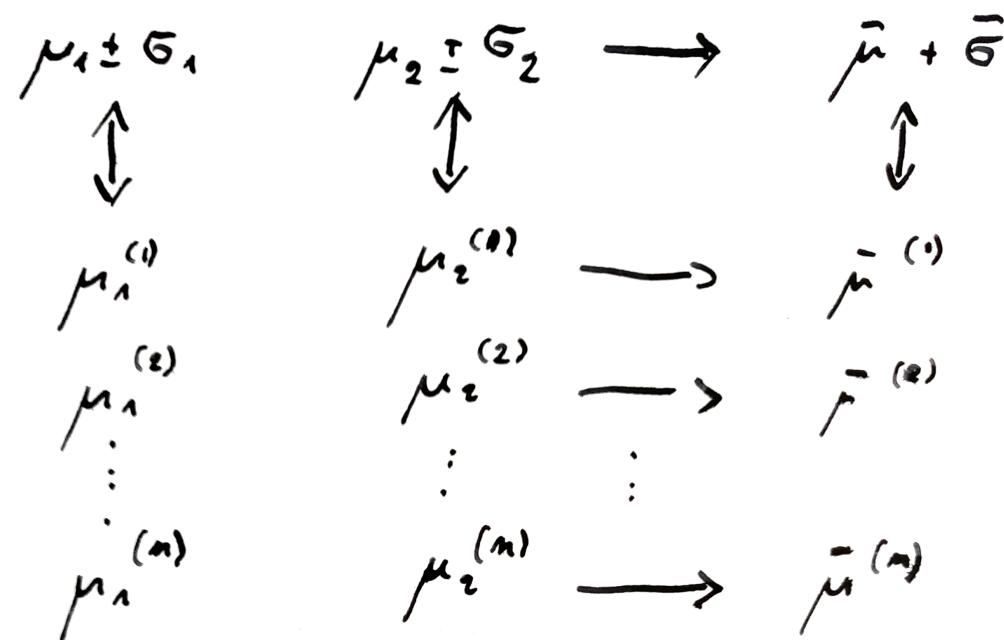


AI SOLUTION

- NEURAL NETWORK REGRESSION
- MONTE CARLO UNCERTAINTIES

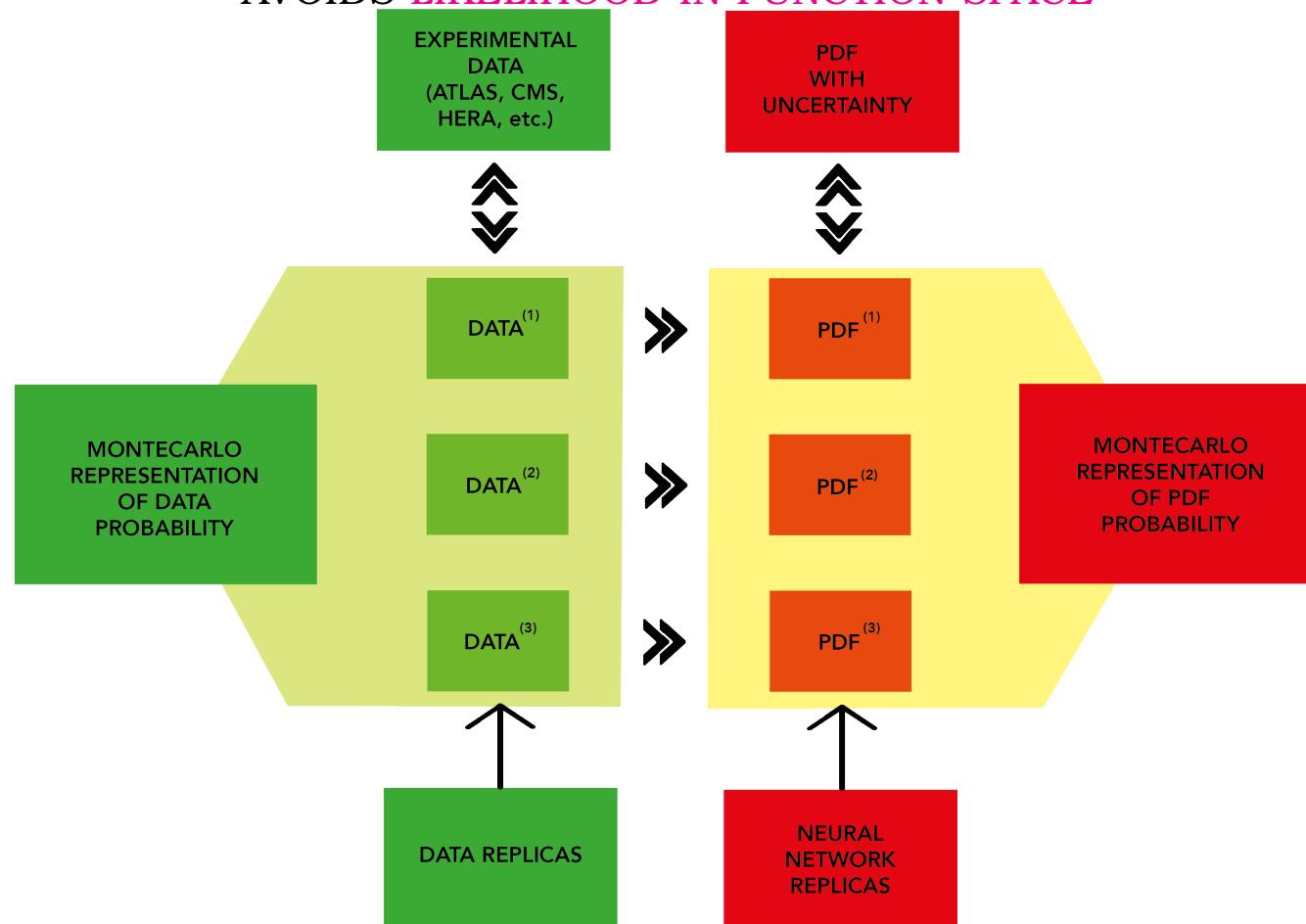
MONTE CARLO COMBINATION

- TWO DATA WITH UNCERTAINTY $z_i = \mu_i \pm \sigma_i$
- SAMPLE OF DATA REPLICAS $\mu_i^{(k)} \rightarrow \mu_i = \langle \mu_i^{(k)} \rangle; \sigma_i^2 = \langle (\mu_i^{(k)} - \mu_i)^2 \rangle.$
- MAP COMBINATION $\mu_1^{(k)}, \mu_2^{(k)} \rightarrow \bar{\mu}^{(k)}$
- $\mu^{(k)}$ REPLICA SAMPLE \Rightarrow REPRESENTATION OF Max A Posteriori PROBABILITY $\bar{\mu} \pm \bar{\sigma}$
 $\bar{\mu} = \langle \bar{\mu}^{(k)} \rangle; \bar{\sigma}^2 = \langle (\bar{\mu}^{(k)} - \bar{\mu})^2 \rangle.$



THE FUNCTIONAL MONTE CARLO

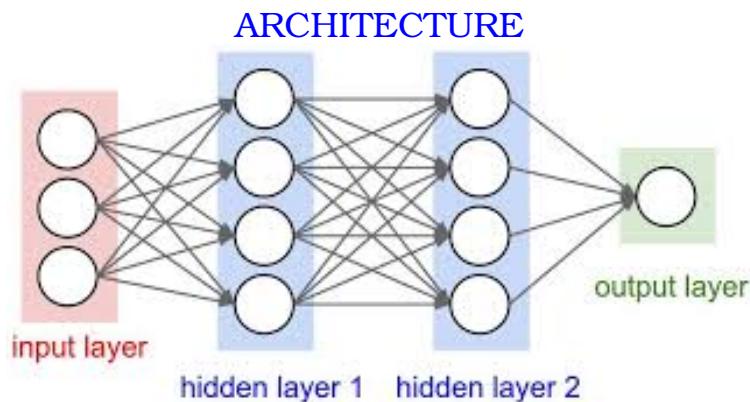
REPLICA SAMPLE OF FUNCTIONS \Leftrightarrow PROBABILITY DENSITY IN FUNCTION SPACE
AVOIDS LIKELIHOOD IN FUNCTION SPACE



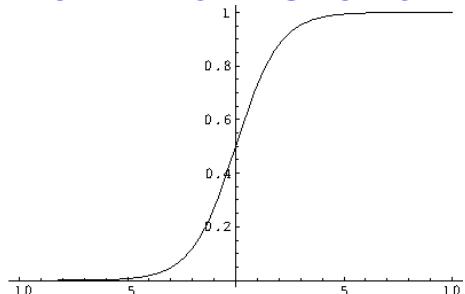
FINAL PDF SET: $f_i^{(a)}(x, \mu)$;

i = up, antiup, down, antidown, strange, antistrange, charm, gluon; $j = 1, 2, \dots N_{\text{rep}}$

FEED-FORWARD NEURAL NETWORKS



ACTIVATION FUNCTION



PARAMETERS

- **WEIGHTS** ω_{ij}
- **THRESHOLDS** θ_i

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

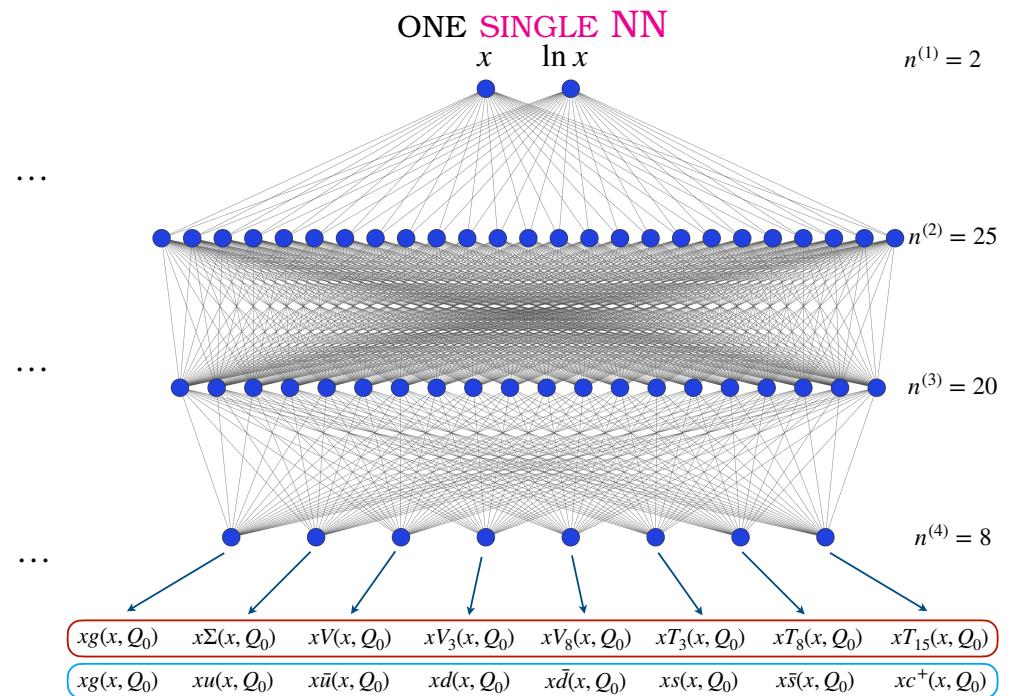
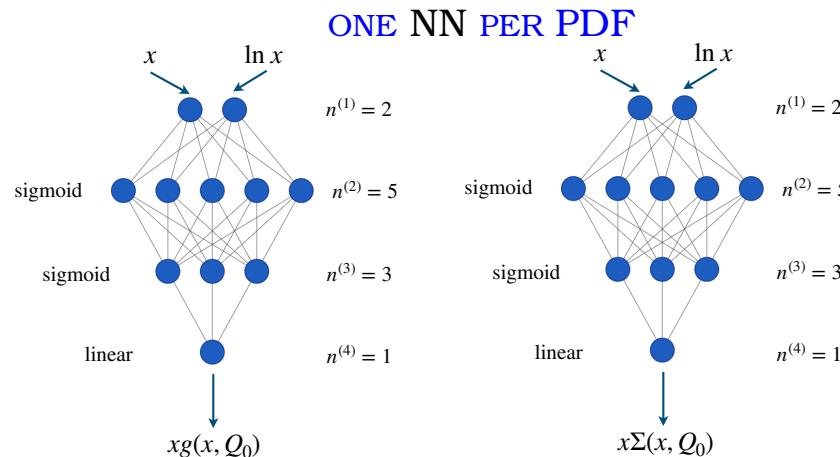
SIMPLEST EXAMPLE

1-2-1

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

NEURAL NETWORKS ARCHITECTURE

- HOW MANY INPUTS?
- HOW MANY INDEPENDENT NNs?



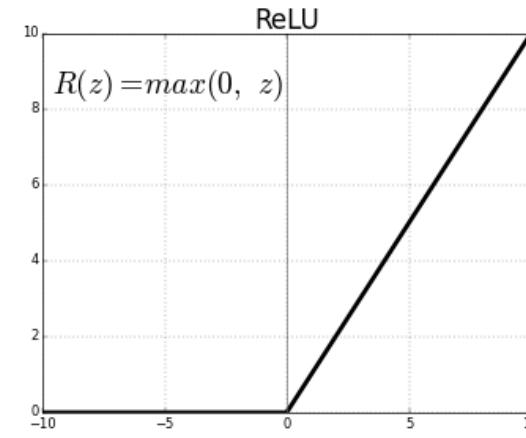
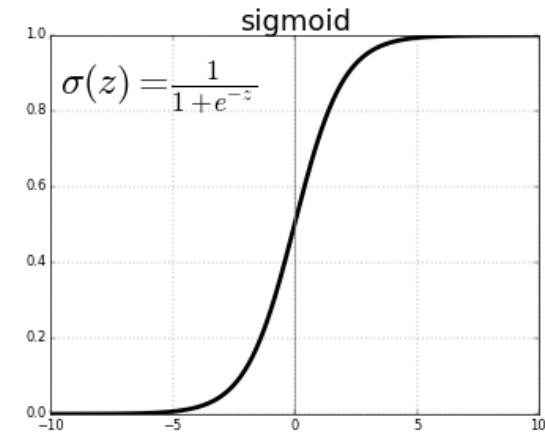
NEURAL NETWORKS

ACTIVATION FUNCTION

- LINEAR ACTIVATION \Rightarrow MULTILINEAR REGRESSION
- + NONLINEAR PROFILE \Rightarrow UNIVERSAL INTERPOL.

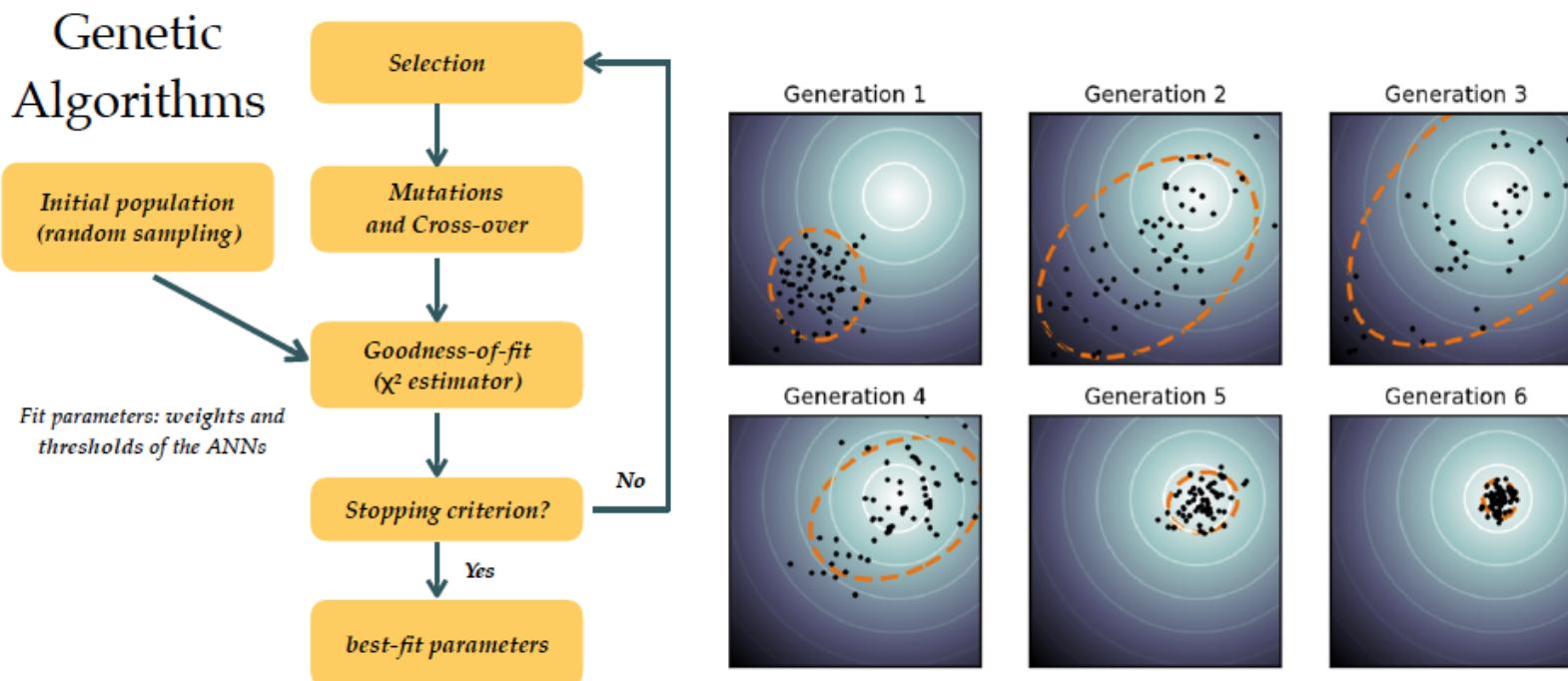
$$F_{\text{out}}^{(i)}(\vec{x}_{\text{in}}) = F \left(\sum_j \omega_{ij} x_{\text{in}}^j - \theta_i \right)$$

- sigmoid $F(x) = \frac{1}{1+e^{-x}}$
- arctan $F(x) = \frac{1}{2} + \frac{1}{\pi} \arctan x$
- RELU $F(x) = \begin{cases} 0; & x < 0 \\ x; & x > 0 \end{cases}$



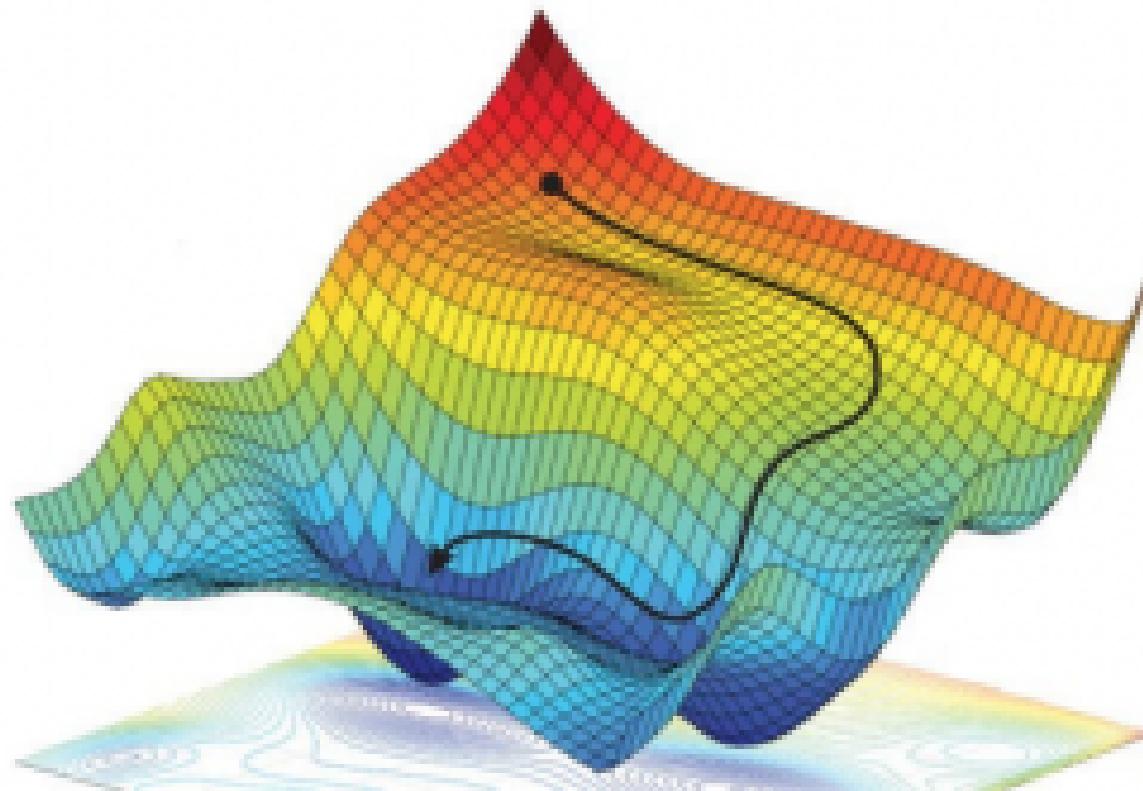
NEURAL NETWORK TRAINING GENETIC ALGORITHMS

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



NEURAL NETWORK TRAINING GRADIENT DESCENT

- BASIC IDEA: COMPUTE GRADIENT OF LOSS W.R. TO PARAMETERS
- SELECT DIRECTION OF DESCENT



NEURAL NETWORK TRAINING MINIMIZATION ALGORITHMS: DESIDERATA

- FAST CONVERGENCE
- DO NOT STOP ON LOCAL MINIMA
- EXPLORE SPACE OF MINIMA (DEGENERATE CASE)

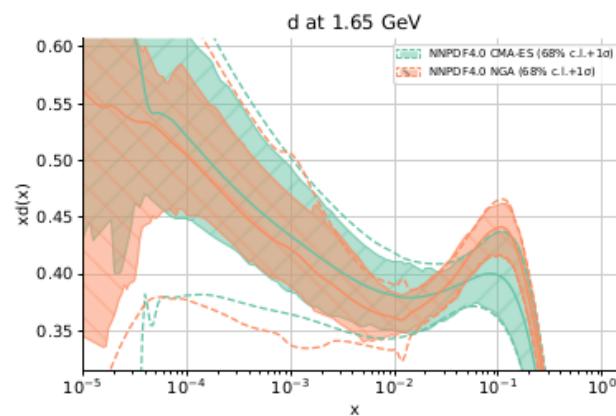
GENETIC ALGORITHMS

- DIFFERENT EPOCHS; VARIABLE MUTATION RATE
- REWEIGHTING DIFFERENT DATA CONTRIBUTIONS TO LOSS
- NODAL MUTATION
- COVARIANCE MATRIX ADAPTATION (CMA)

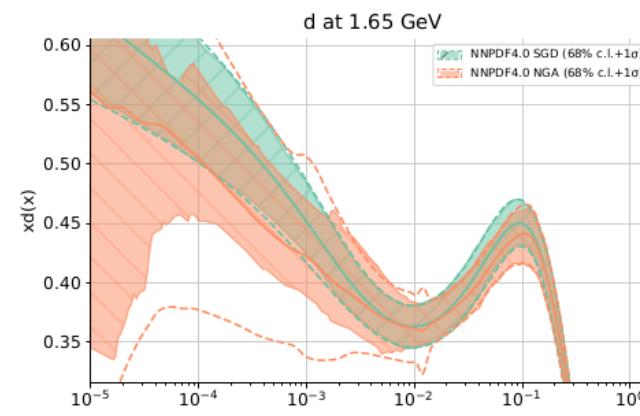
GRADIENT DESCENT

- GLOROT NORMAL/UNIFORM INITIALIZATION
- ADAPTIVE GRADIENT / ADAPTIVE MOMENT
- STOCHASTIC GD
- BATCH GD

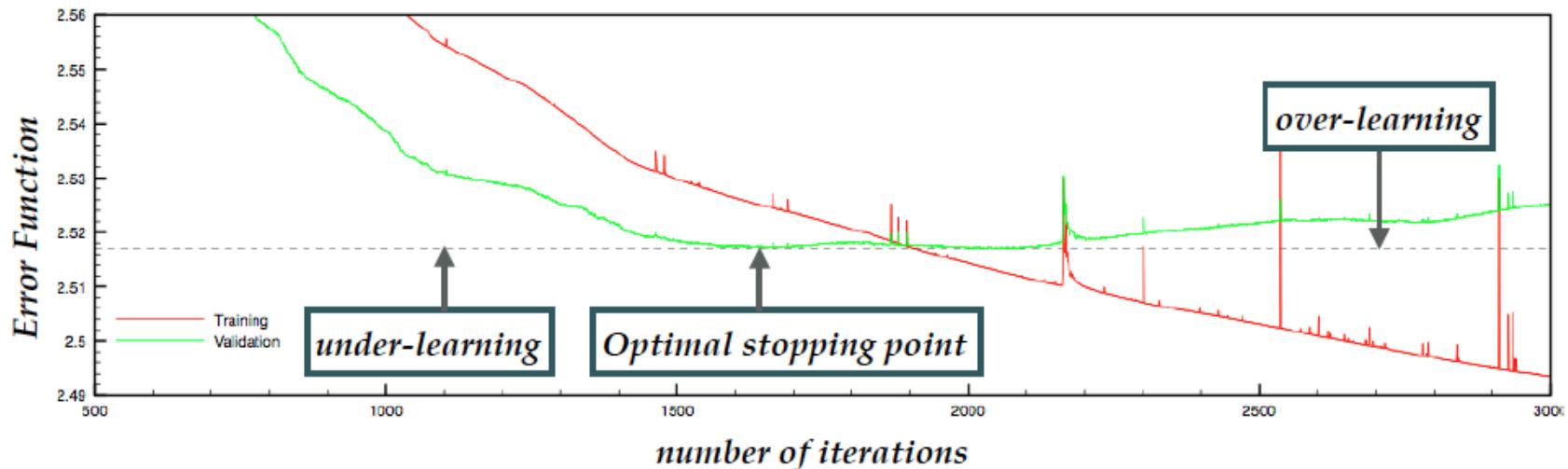
NAIVE GA VS. CMA



GA (NAIVE) VS GD (ADADELTA)



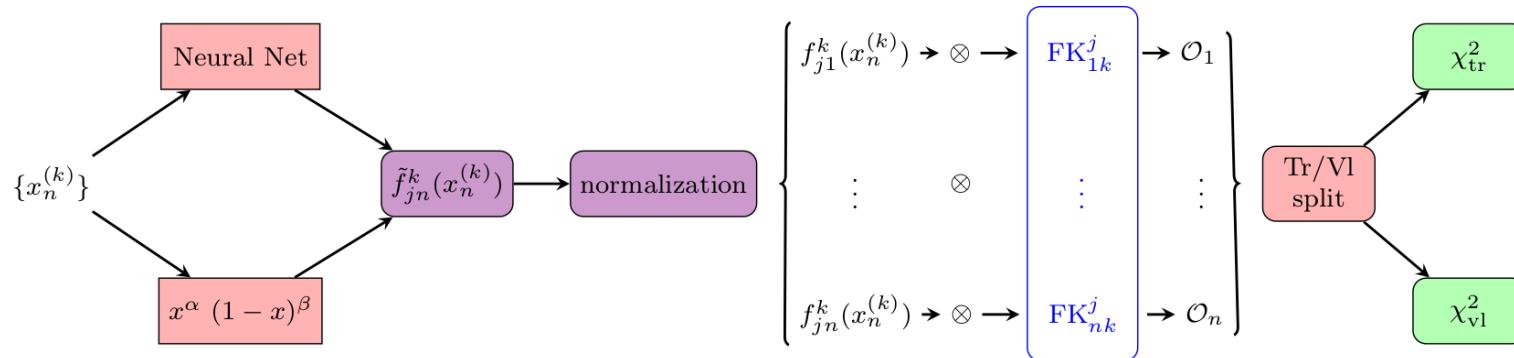
NEURAL NETWORK TRAINING OVERLEARNING AND CROSS-VALIDATION



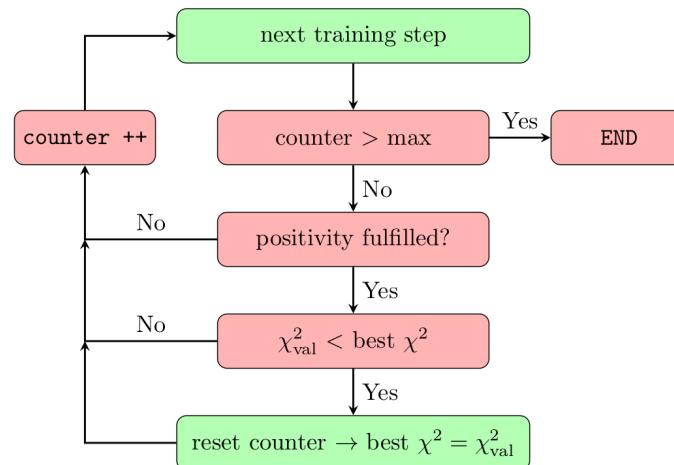
- NEURAL NET TRAINING \Rightarrow LOSS MINIMIZATION (χ^2)
- RANDOM TRAINING-VALIDATION SPLIT, TRAINING LOSS MINIMIZED
- TRAINING STOPS AT MIMUMUM OF VALIDATION LOSS

PDFS AND MACHINE LEARNING

NEURAL NETS FOR PDFS THE ALGORITHM



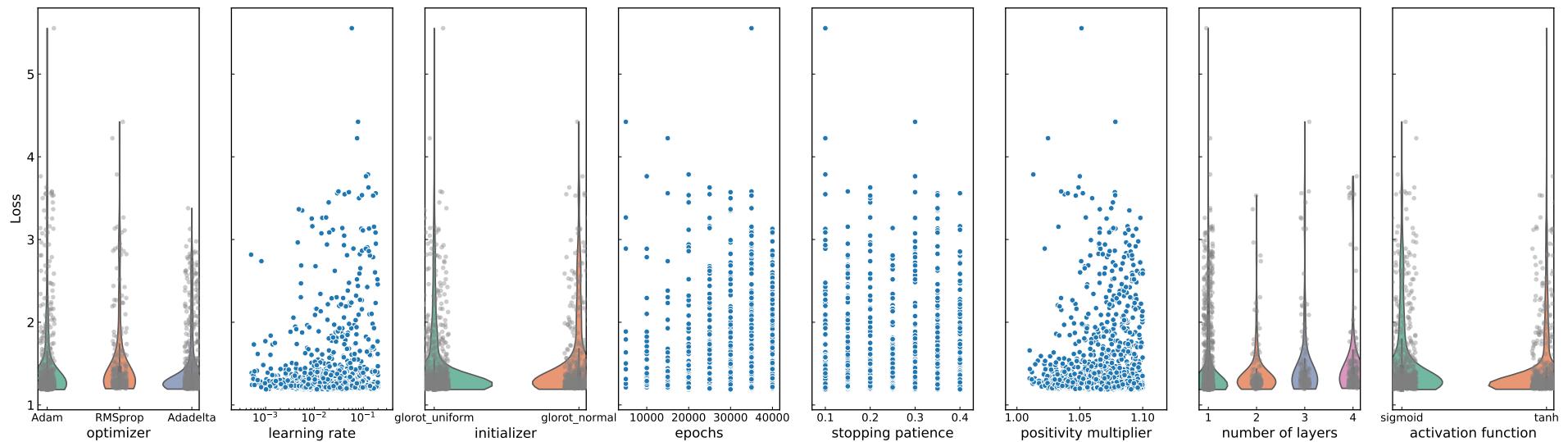
STOPPING



THE HYPERPARAMETERS

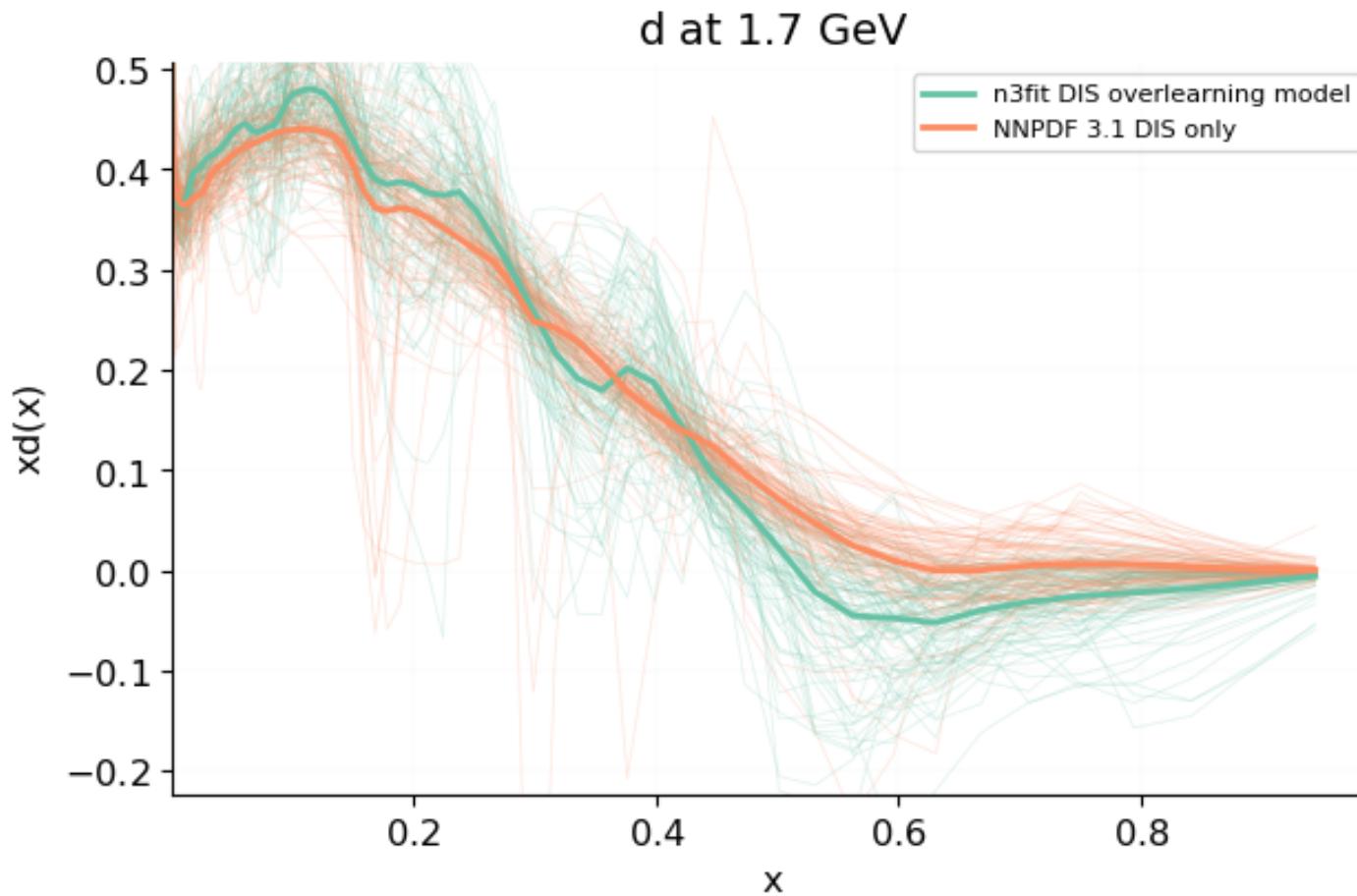
MODEL	MINIMIZATION
Number of layers	Optimizer
Size of each layer	Initializer
Activation functions	Learning rate
Initial positivity	Clipnorm
Initial integrability	Maximum number of epochs
	Stopping Patience

HYPERPARAMETER OPTIMIZATION



- BAYESIAN SCAN OF PARAMETER SPACE
- OPTIMIZE LOSS: VALIDATION χ^2

RESULTS: OVERFITTING! DOWN QUARK: HYPEROPTIMIZED VS. HAND-PICKED



- **HAND-PICKED:** WIGGLES: FINITE SIZE \Rightarrow WILL GO AWAY AS N_{rep} GROWS
- **HYPEROPT:** WIGGLY PDFS \Leftrightarrow OVERFITTING \Rightarrow WILL NOT GO AWAY
($\chi^2_{\text{train}} \ll \chi^2_{\text{valid}}$ EVEN THOUGH VALIDATION LOSS MINIMIZED)

WHAT HAPPENED?

OPTIMIZATION

PDF fit optimization $\xrightarrow{\text{Target}}$ low χ^2_{train}

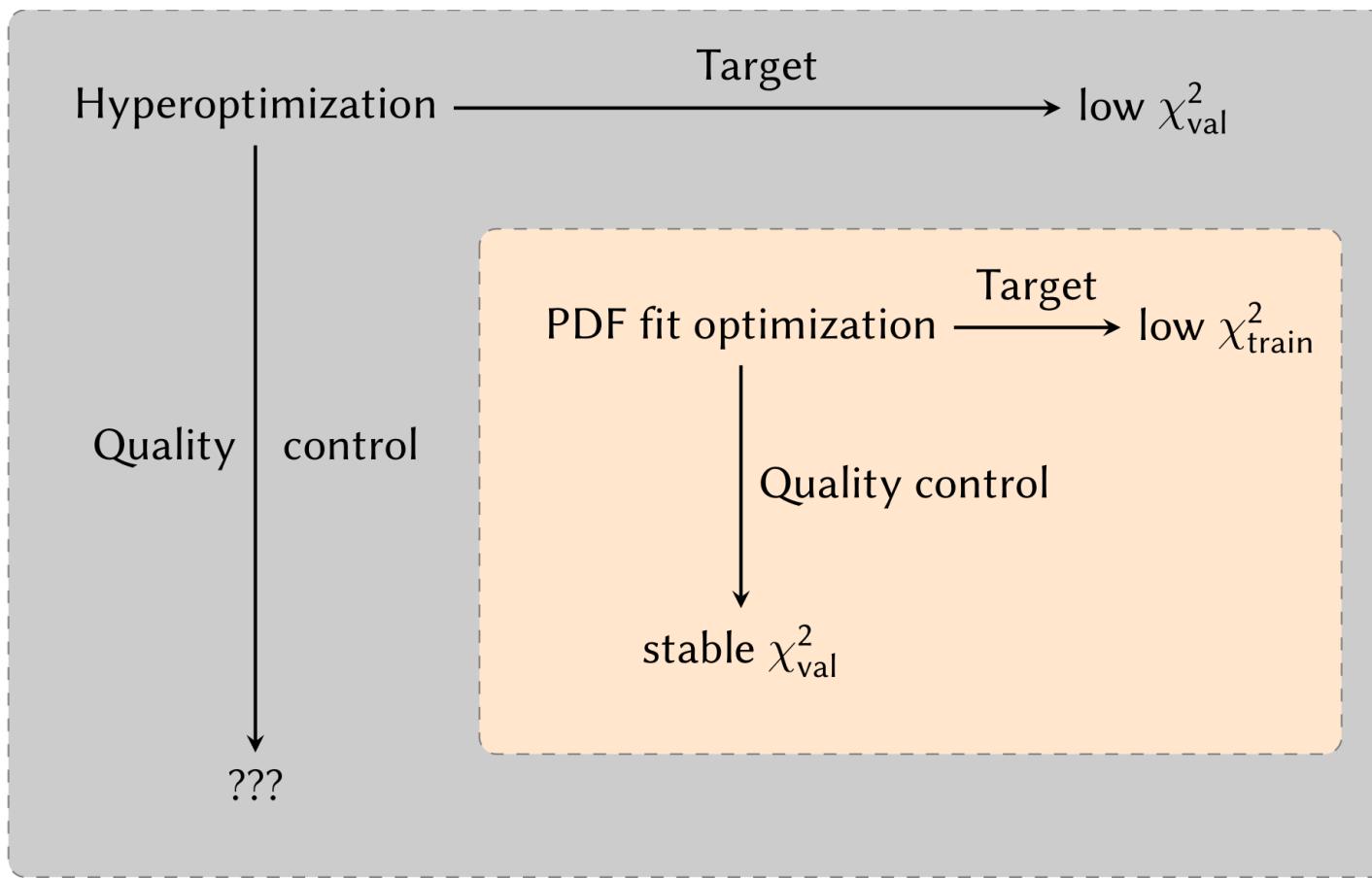
↓
Quality control

stable χ^2_{val}

CROSS-VALIDATION SELECTS THE OPTIMAL MINIMUM

WHAT HAPPENED?

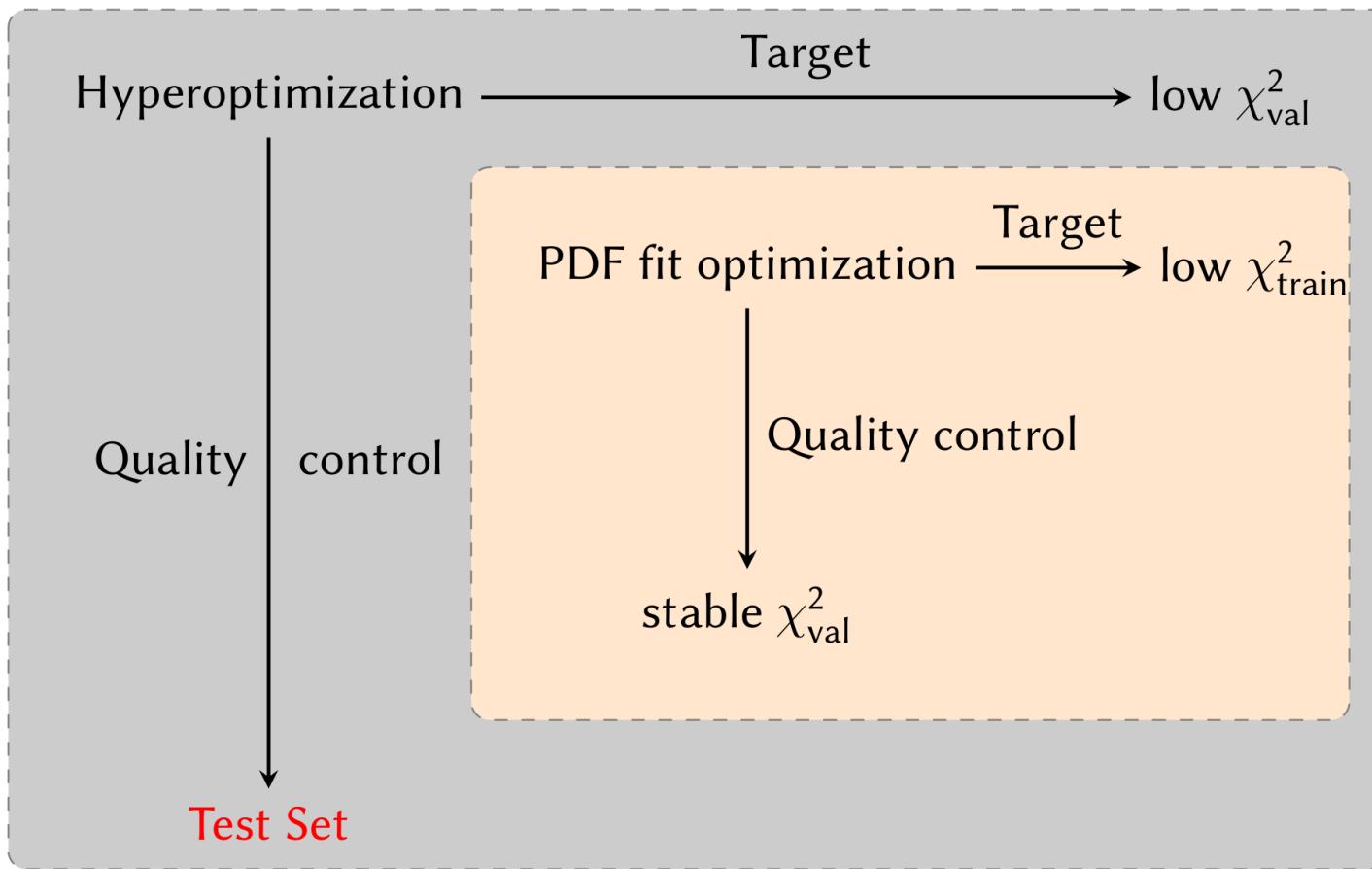
HYPEROPTIMIZATION



WE ARE MISSING A CONTROL CRITERION

THE SOLUTION

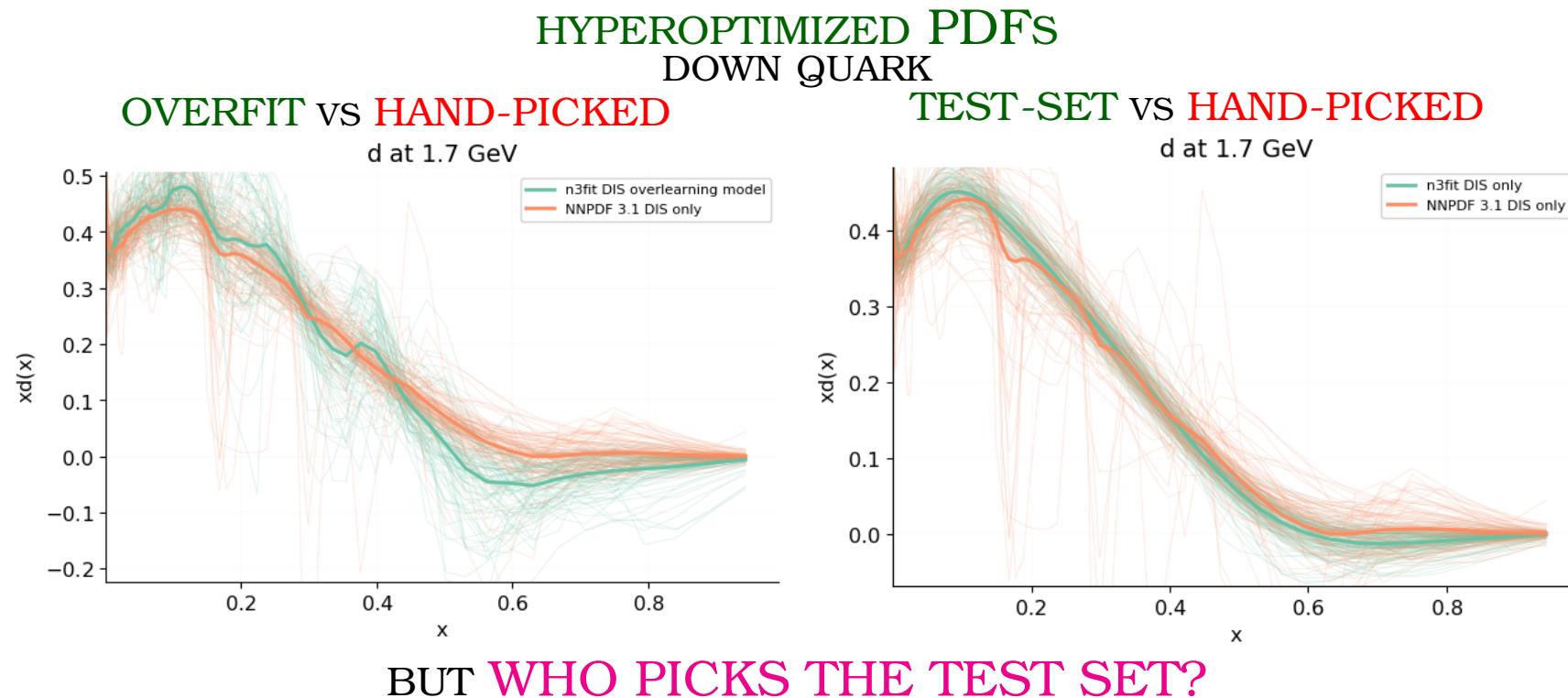
THE TEST SET



COMPARE TO A **TEST SET** \Rightarrow NEW DATA PREVIOUSLY NOT USED AT ALL
TESTS **GENERALIZATION POWER**

TEST SET RESULTS

- COMPLETELY UNCORRELATED TEST SET
- OPTIMIZE ON WEIGHTED AVERAGE OF VALIDATION AND TEST
⇒ NO OVERLEARNING



K-FOLDS

THE BASIC IDEA:

- DIVIDE THE DATA INTO k REPRESENTATIVE SUBSETS
EACH CONTAINING PROCESS TYPES, KINEMATIC RANGE OF FULL SET
- TRAIN $k - 1$ SETS AND USE k -TH SET AS TEST
 $\Rightarrow k$ VALUES OF $\chi^2_{\text{test}, i}$

Fold 1		
CHORUS σ_{CC}^ν	HERA I+II inc NC e^+p 920 GeV	BCDMS p
LHCb Z 940 pb	ATLAS W, Z 7 TeV 2010	CMS Z p_T 8 TeV (p_T^{ll}, y_{ll})
DY E605 σ_{DY}^p	CMS Drell-Yan 2D 7 TeV 2011	CMS 3D dijets 8 TeV
ATLAS single- $t\bar{t}$ y (normalised)	ATLAS single top R_t 7 TeV	CMS $t\bar{t}$ rapidity $y_{t\bar{t}}$
CMS single top R_t 8 TeV		

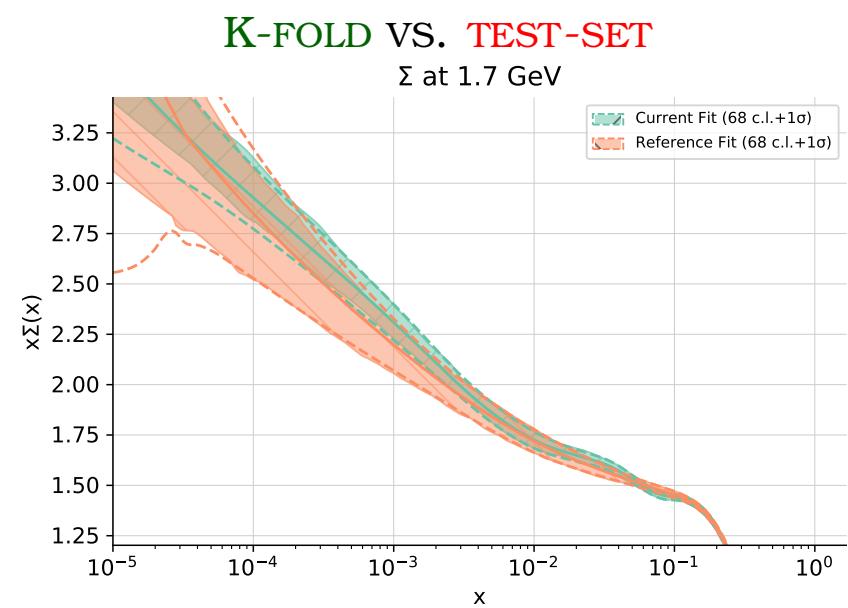
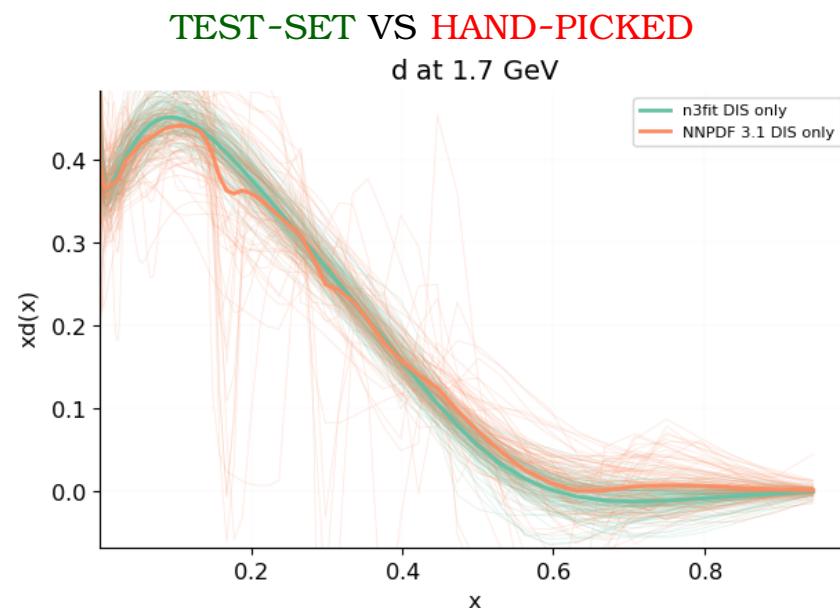
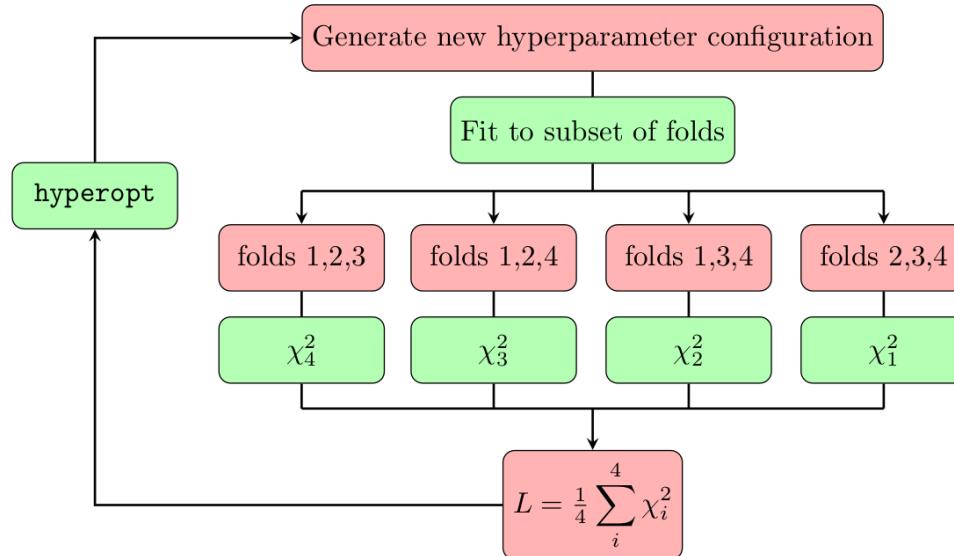
Fold 2		
HERA I+II inc CC e^-p	HERA I+II inc NC e^+p 460 GeV	HERA comb. σ_{bb}^{red}
NMC p	NuTeV σ_c^p	LHCb $Z \rightarrow ee$ 2 fb
CMS W asymmetry 840 pb	ATLAS Z p_T 8 TeV (p_T^{ll}, M_{ll})	D0 $W \rightarrow \mu\nu$ asymmetry
DY E886 σ_{DY}^p	ATLAS direct photon 13 TeV	ATLAS dijets 7 TeV, R=0.6
ATLAS single antitop y (normalised)	CMS σ_{tt}^{tot}	CMS single top $\sigma_t + \sigma_{t\bar{t}}$ 7 TeV

Fold 3		
HERA I+II inc CC e^+p	HERA I+II inc NC e^+p 575 GeV	NMC d/p
NuTeV σ_c^ν	LHCb $W, Z \rightarrow \mu$ 7 TeV	LHCb $Z \rightarrow ee$
ATLAS W, Z 7 TeV 2011 Central selection	ATLAS W^+ +jet 8 TeV	ATLAS HM DY 7 TeV
CMS W asymmetry 4.7 fb	DY E866 $\sigma_{\text{DY}}^d / \sigma_{\text{DY}}^p$	CDF Z rapidity (new)
ATLAS σ_{tt}^{tot}	ATLAS single top y_t (normalised)	CMS σ_{tt}^{tot} 5 TeV
CMS $t\bar{t}$ double diff. ($m_{t\bar{t}}, y_t$)		

Fold 4		
CHORUS σ_{CC}^ν	HERA I+II inc NC e^+p 820 GeV	LHCb $W, Z \rightarrow \mu$ 8 TeV
LHCb $Z \rightarrow \mu\mu$	ATLAS W, Z 7 TeV 2011 Fwd	ATLAS W^- +jet 8 TeV
ATLAS low-mass DY 2011	ATLAS Z p_T 8 TeV (p_T^{ll}, y_{ll})	CMS W rapidity 8 TeV
D0 Z rapidity	CMS dijets 7 TeV	ATLAS single top y_t (normalised)
ATLAS single top R_t 13 TeV	CMS single top R_t 13 TeV	

K-FOLD VALIDATION

LOSS: AVERAGE χ^2 OF NON-FITTED FOLDS

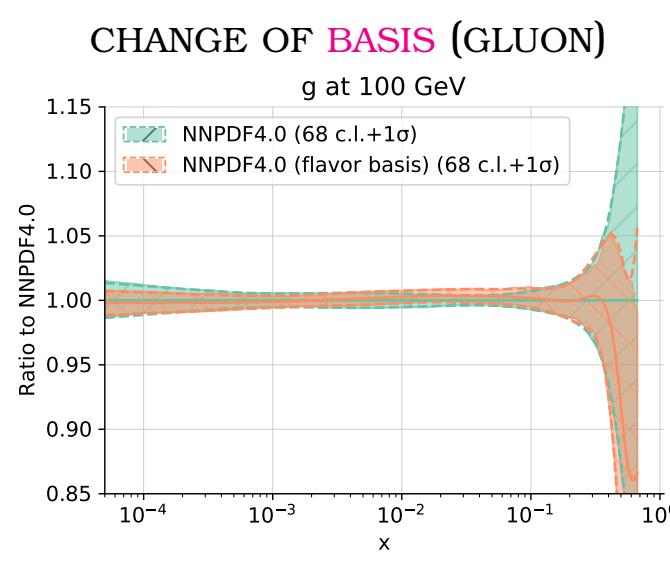
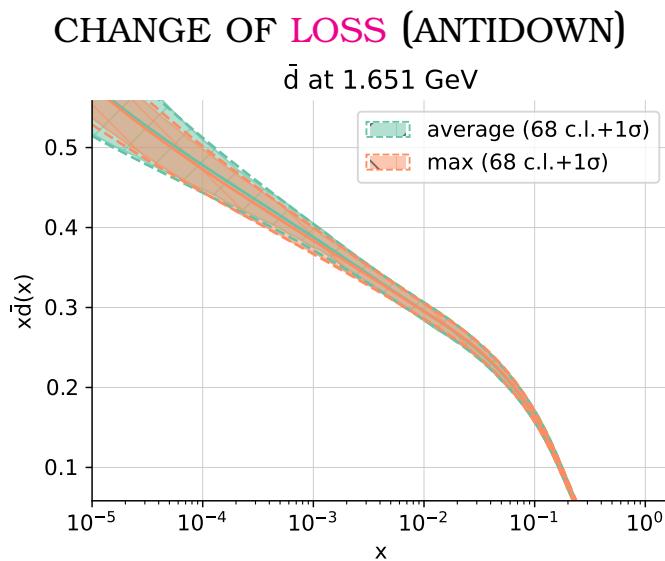


K-FOLD VALIDATION: RESULTS AND STABILITY

HYPEROPTIMIZED PARAMETERS

Parameter	NNPDF4.0	L as in Eq. (3.21)	Flavour basis Eq. (3.2)
Architecture	25-20-8	70-50-8	7-26-27-8
Activation function	hyperbolic tangent	hyperbolic tangent	sigmoid
Initializer	glorot_normal	glorot_uniform	glorot_normal
Optimizer	Nadam	Adadelta	Nadam
Clipnorm	6.0×10^{-6}	5.2×10^{-2}	2.3×10^{-5}
Learning rate	2.6×10^{-3}	2.5×10^{-1}	2.6×10^{-3}
Maximum # epochs	17×10^3	45×10^3	45×10^3
Stopping patience	10% of max epochs	12% of max epochs	16% of max epochs
Initial positivity $\Lambda^{(\text{pos})}$	185	106	2
Initial integrability $\Lambda^{(\text{int})}$	10	10	10

- DIFFERENT CHOICES OF LOSS: $L = \frac{1}{n_{\text{fold}}} \sum_{k=1}^{n_{\text{fold}}} \chi_k^2$ vs. $L = \max(\chi_1^2, \chi_2^2, \chi_3^2, \dots, \chi_{n_{\text{fold}}}^2)$
- PDF FLAVOR VS. EVOLUTION BASIS



**VALIDATING AND
UNDERSTANDING**

VALIDATION CLOSURE TESTS

- ASSUME UNDERLYING “TRUTH” PDF (SAY A RANDOM PDF REPLICA)
- GENERATE DATA WITH STATISTICAL AND SYSTEMATIC SHIFTS
- DETERMINE PDFs & COMPARED TO “TRUTH”

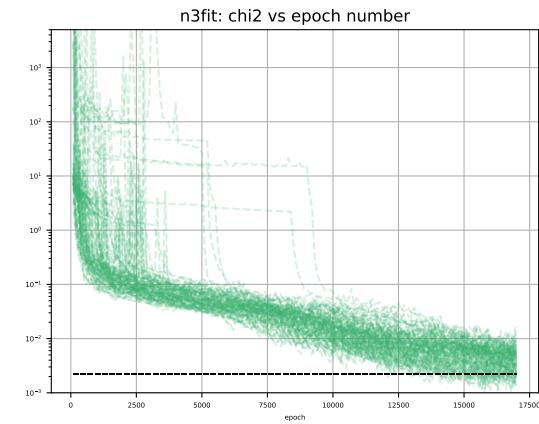
THE NATURE OF UNCERTAINTIES

- LEVEL 0:
 - DATAPoint EQUAL TO THE “TRUTH VALUE”; ZERO UNCERTAINTY
 - MUST FIND $\chi^2 = 0$ (“TRUTH”)
 - INTERPOLATION/EXTRAPOLATION UNCERTAINTY
- LEVEL 1:
 - PSEUDO- DATAPoints \Rightarrow FLUCTUATIONS ABOUT “TRUTH”
 \Rightarrow “RUN OF THE UNIVERSE”
 - FIT DATA OVER AND OVER AGAIN
 - $\chi^2 \approx 1$
 - FUNCTIONAL UNCERTAINTY
- LEVEL 2:
 - DATA AS IN LEVEL 1
 - DATA REPLICAS OF THESE “DATA”
 - FIT PDF REPLICAS TO DATA REPLICAS
 - $\chi^2 \approx 2$ REPLICA TO REPLICA; $\chi^2 \approx 1$ AVERAGE TO TRUTH
 - DATA UNCERTAINTY

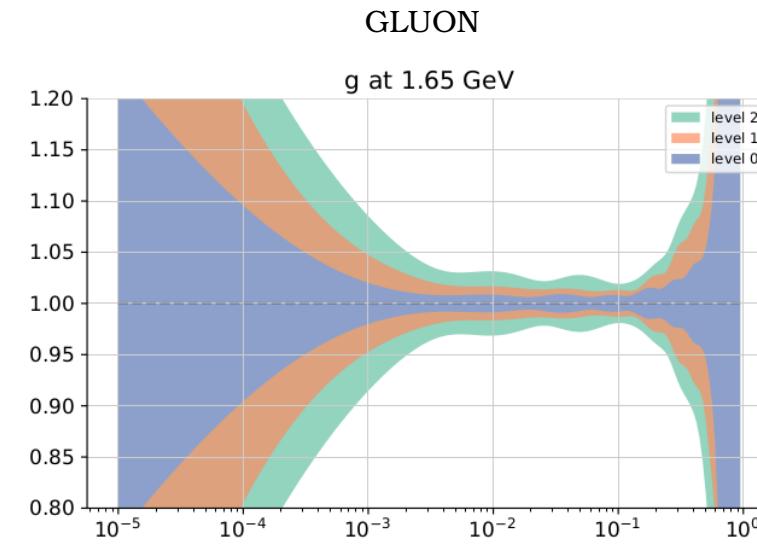
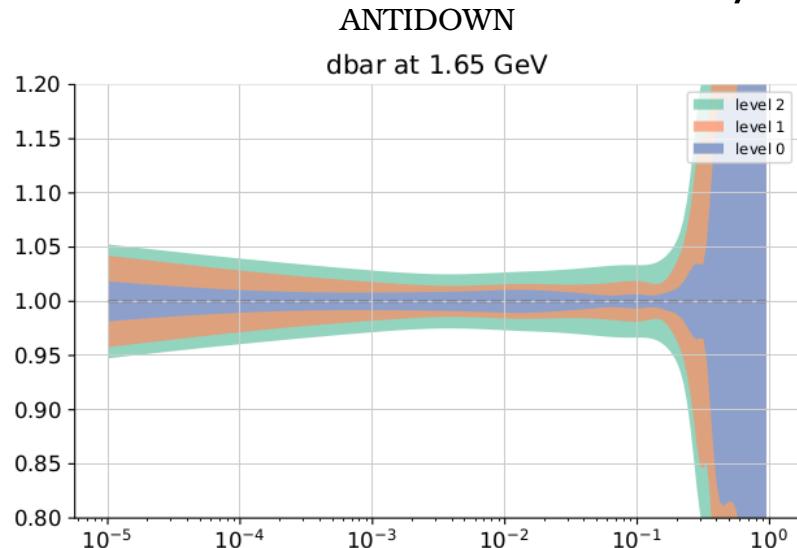
UNCERTAINTIES: TYPE AND SIZE CLOSURE TEST RESULTS (NNPDF4.0)

LEVEL 0 χ^2 VS TRAINING

- LEVEL 0 (TRUTH DATA) $\Rightarrow \chi^2 \approx 0$, YET UNCERTAINTY NONZERO
 \Rightarrow NEURAL NETS \Leftrightarrow MANY FUNCTIONAL FORMS
- LEVEL 1 (RUNS OF UNIVERSE) \Rightarrow REPLICAS ALL FITTED TO SAME DATA,
YET UNCERTAINTY NONZERO
 \Rightarrow DITTO
- LEVEL 0, 1 AND 2 UNCERTAINTIES COMPARABLE IN SIZE

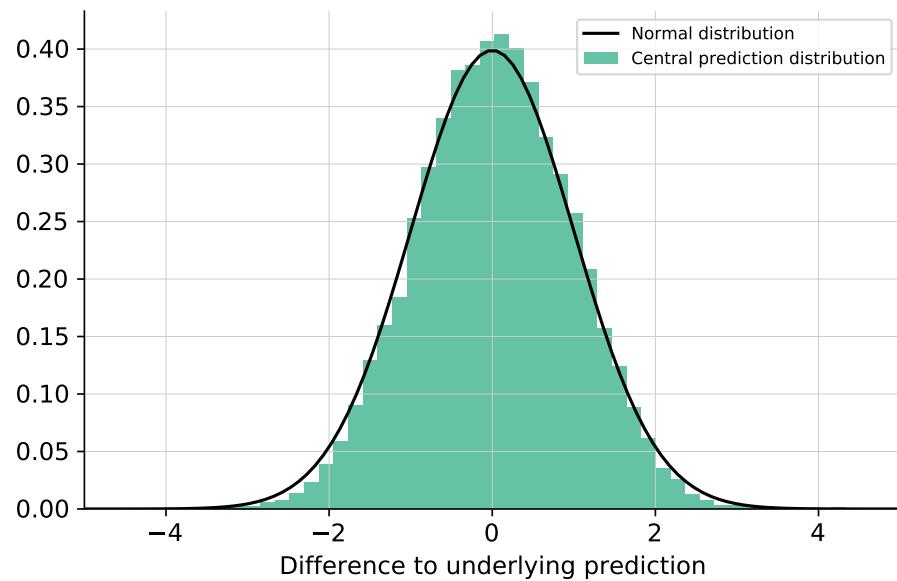


LEVEL 0/1/2 UNCERTAINTIES

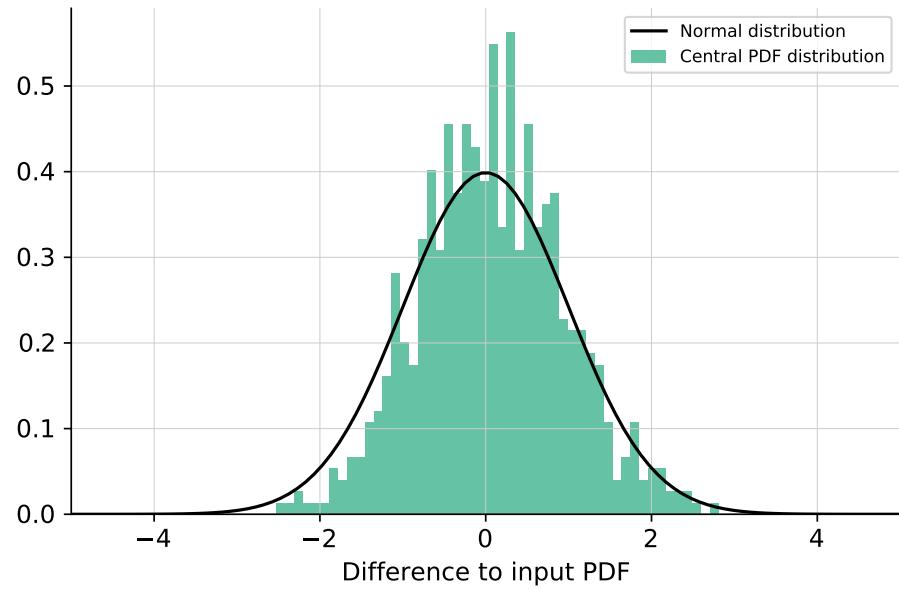


TESTING: THE INDICATORS DISTRIBUTION OF DEVIATIONS FROM TRUTH

DATA SPACE (OUT OF SAMPLE)



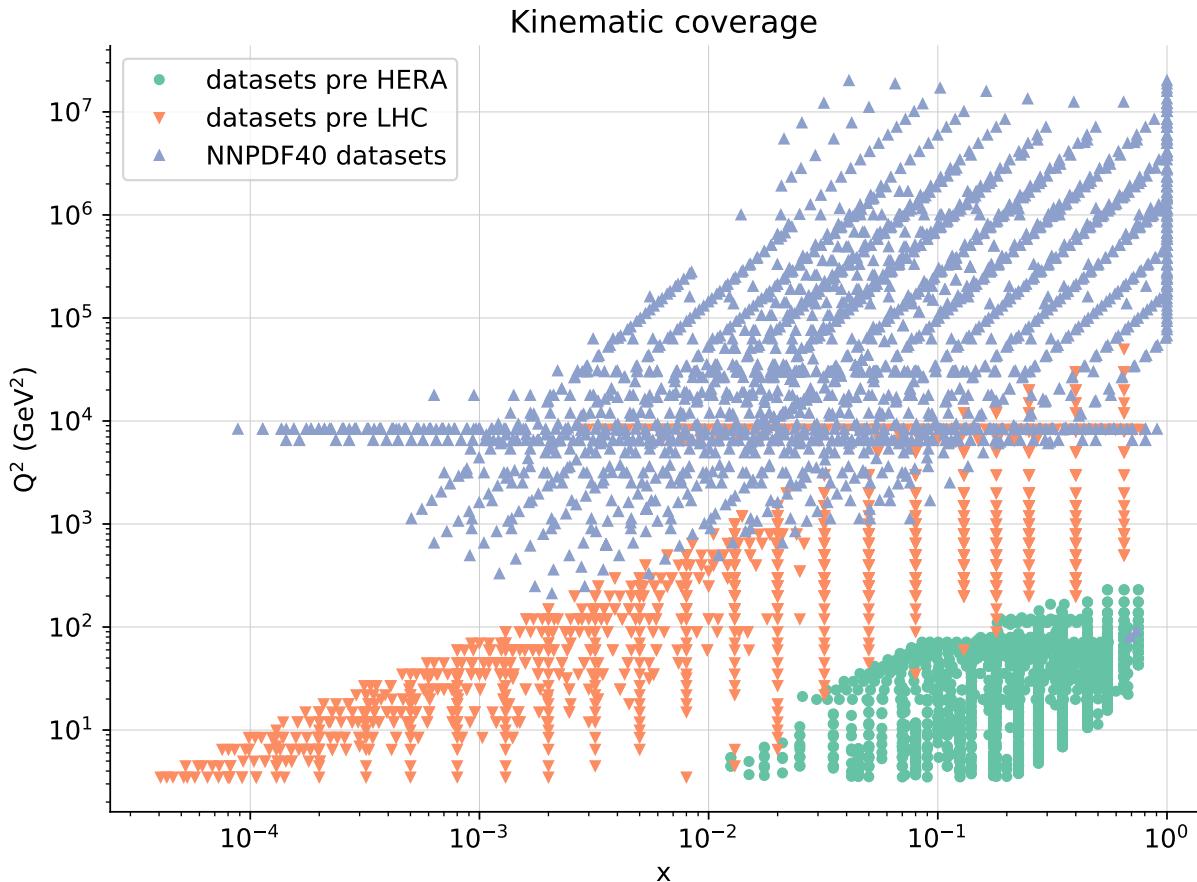
PDF SPACE



- PDF-SPACE MORE NOISY THAN DATA SPACE

FUTURE TESTS

IDEA: USE (REAL) HIERARCHICAL DATASETS

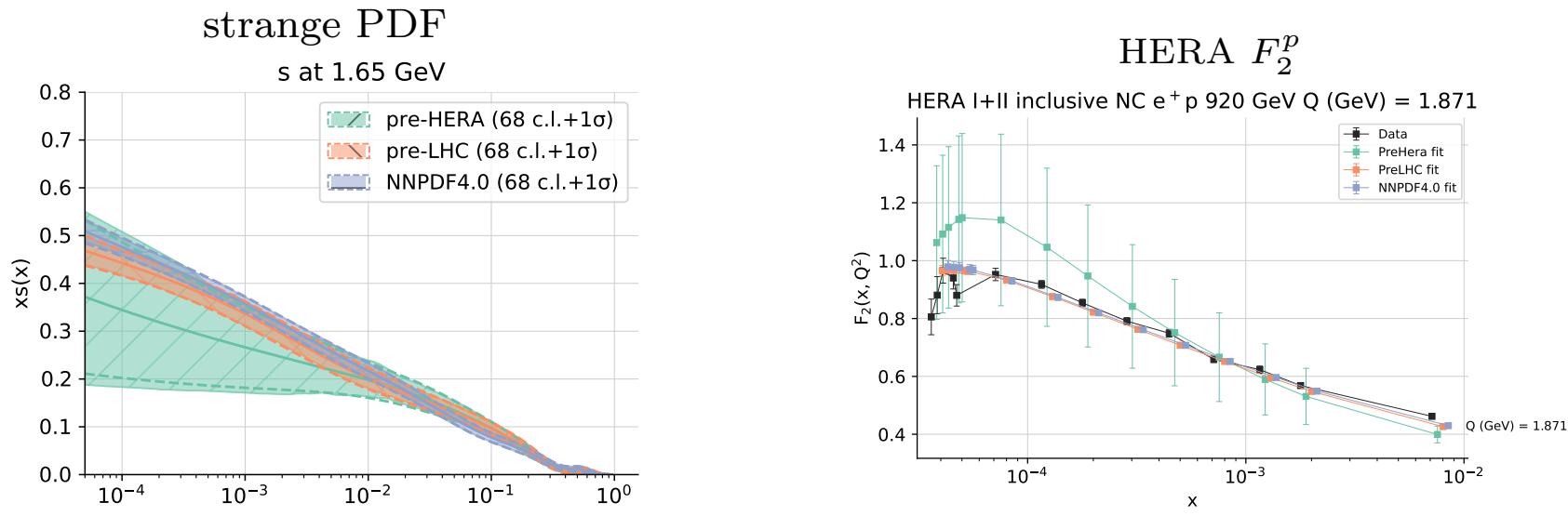


- DEFINE “PRE-HERA”, “PRE-LHC” AND “CURRENT” DATASETS
EACH LATER DATASET IS EXTRAPOLATION OF PREVIOUS
- DETERMINE PDFs & COMPARE TO “FUTURE” DATA
- COMPUTE χ^2 TO FUTURE DATA:
 - WITHOUT PDF UNCERTAINTIES \Rightarrow IF $\gg 1$, MISSING INFORMATION
 - WITH PDF UNCERTAINTY \Rightarrow IF ~ 1 , TEST PASSED
MISSING INFO REPRODUCED BY UNCERTAINTY

ASSESSING EXTRAPOLATION UNCERTAINTIES FUTURE TEST RESULTS (NNPDF4.0)

χ^2 : FITTED VS EXTRAPOLATED: WITHOUT/WITH PDF UNC.

PROCESS	PRE-HERA	PRE-LHC	NNPDF4.0
FT DIS (NC)	1.05	1.18	1.23
FT DIS (CC)	0.80	0.85	0.87
FT DY	0.92	1.27	1.59
HERA	27.20/1.23	1.22	1.20
COLL. DY (TEV.)	5.52/1.02	0.99	1.11
COLL. DY (LHC)	18.91/1.31	2.63/1.58	1.53
TOP QUARK	20.01/1.06	1.30/0.87	1.01
JETS	2.69/0.98	2.12/1.10	1.26
TOTAL OUT OF SAMPLE	19.48/1.16	2.10/1.15	-



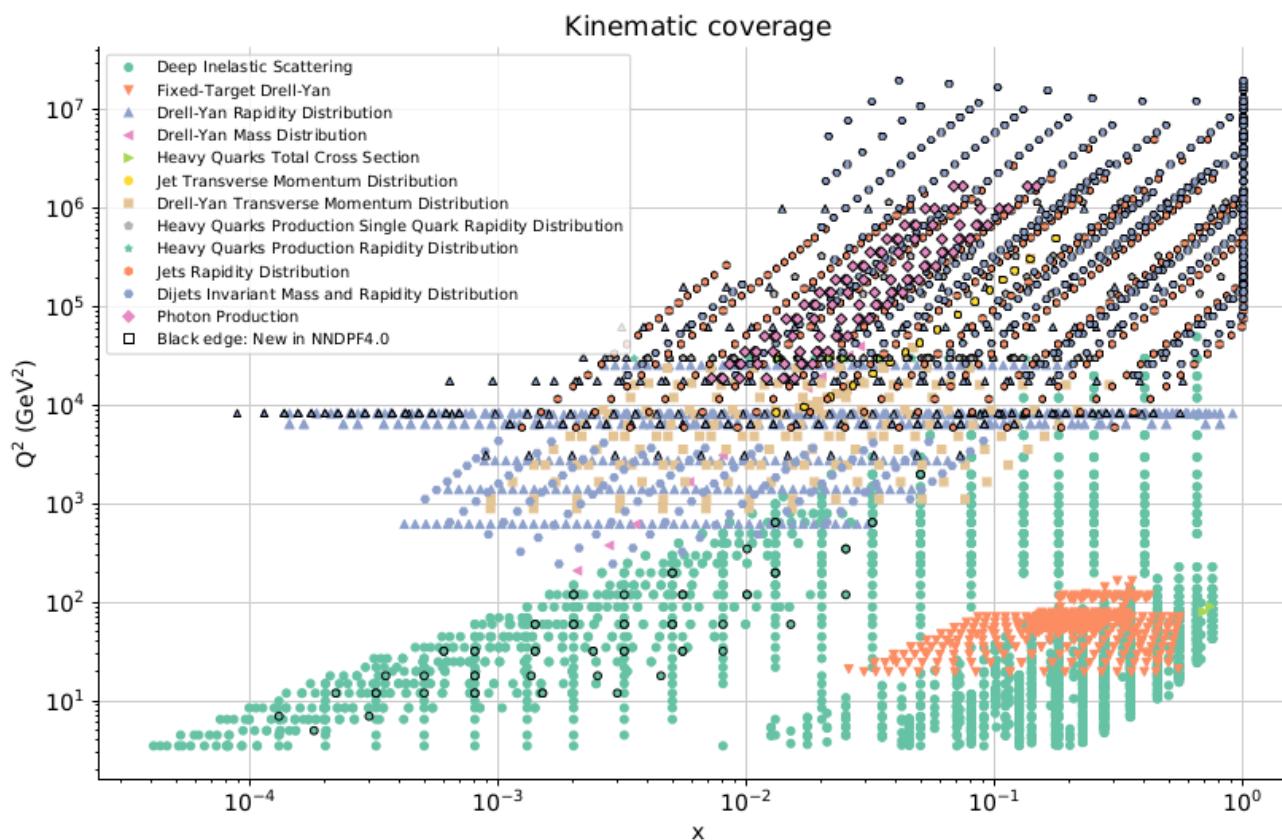
ML PREDICTS THE RISE OF F_2 AT HERA

PDFS TODAY

CONTEMPORARY PDF DETERMINATION

THE DATA

Experimental data in NNPDF4.0

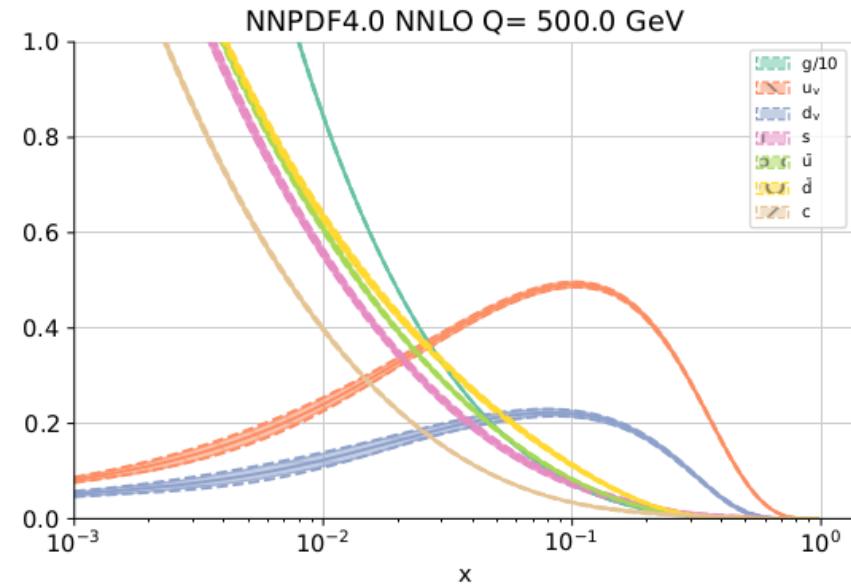
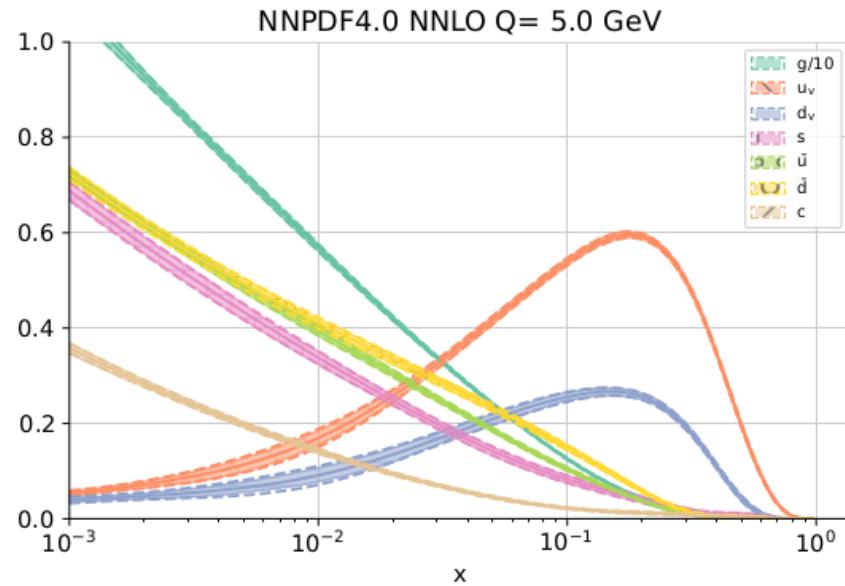


More than 4000 datapoints!

New processes:

- direct photon
- single top
- dijets
- W+jet
- DIS jet

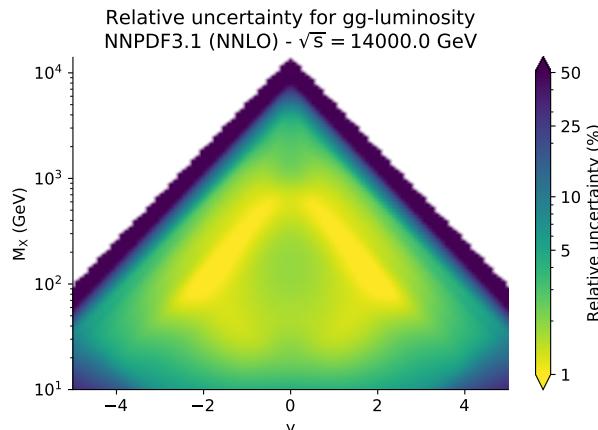
CONTEMPORARY PDF DETERMINATION THE PDFs



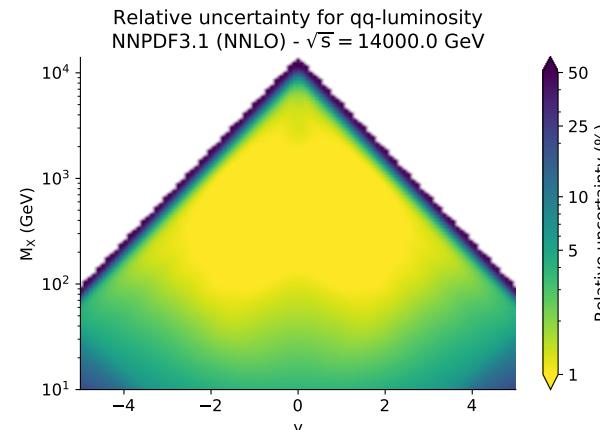
CONTEMPORARY PDF DETERMINATION

THE UNCERTAINTIES (2016)

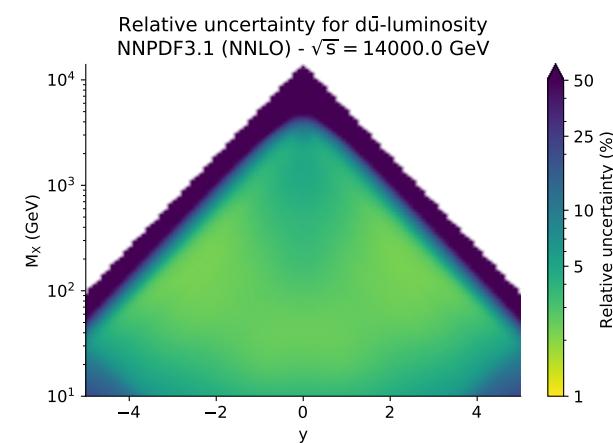
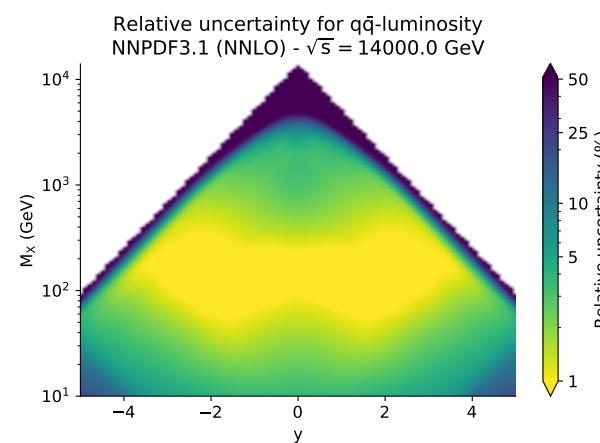
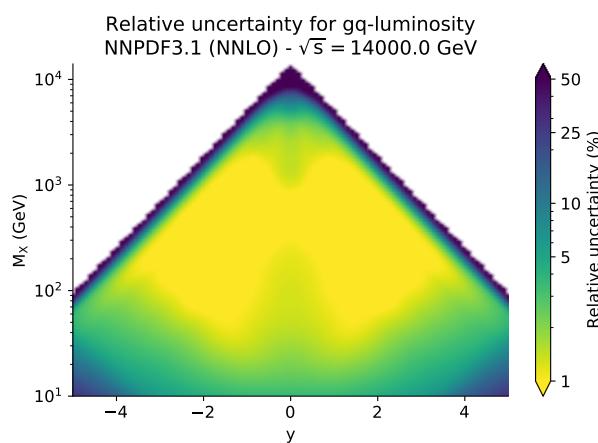
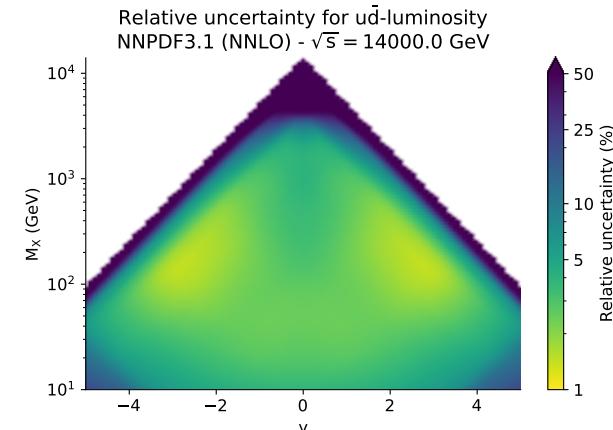
GLUON



SINGLET



FLAVORS

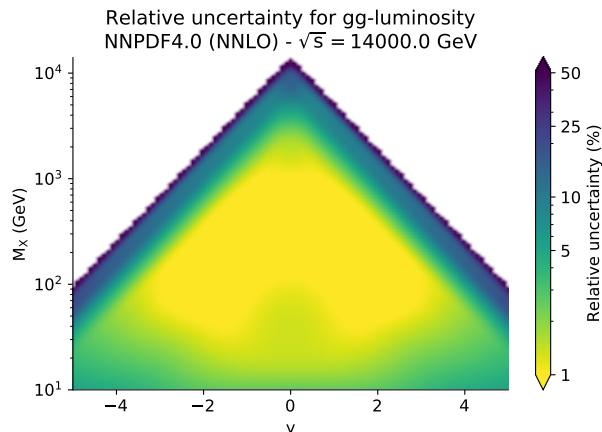


- TYPICAL UNCERTAINTIES IN DATA REGION: SINGLET $\sim 3\%$, NONSINGLET $\sim 5\%$
- DATA REGION: $10^2 \lesssim M_X \lesssim 10^3$ TeV, $-2 \lesssim y \lesssim 2$

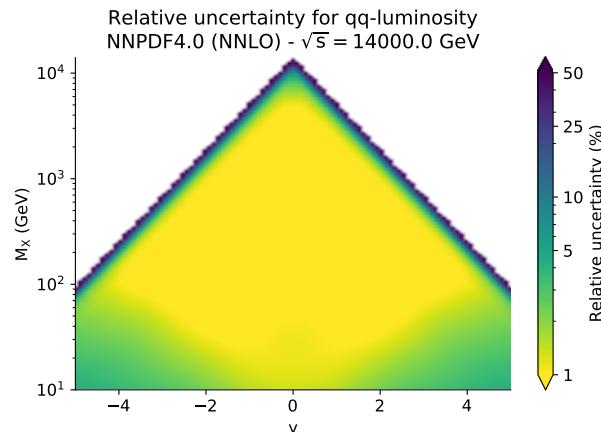
CONTEMPORARY PDF DETERMINATION

THE UNCERTAINTIES (2022)

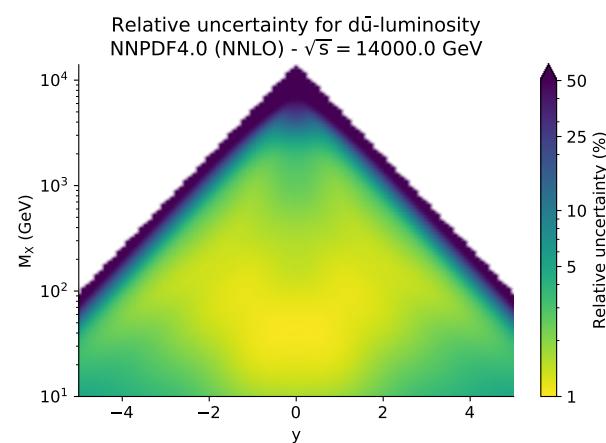
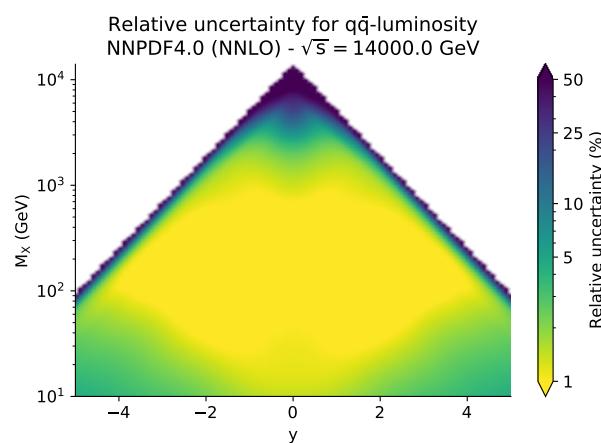
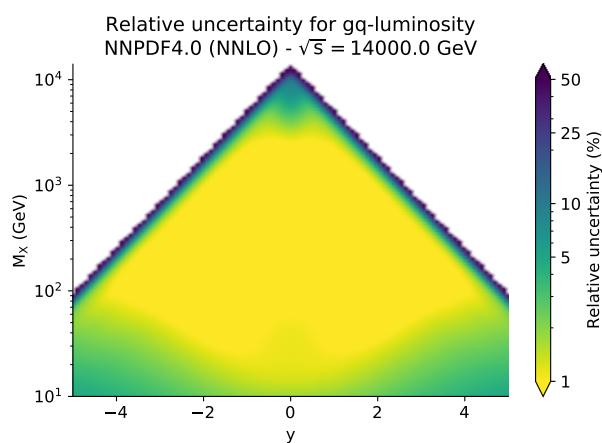
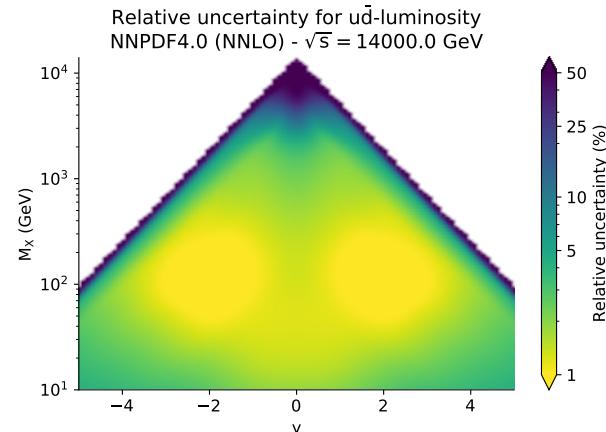
GLUON



SINGLET



FLAVORS

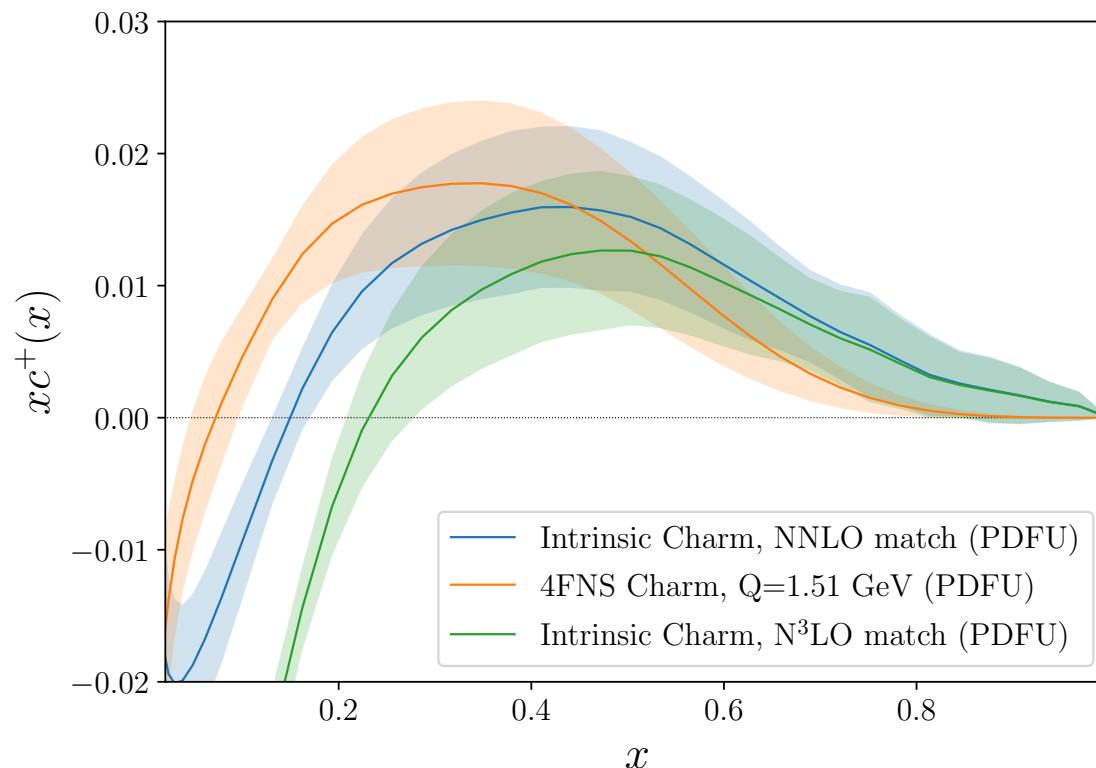


- TYPICAL UNCERTAINTIES IN DATA REGION: SINGLET $\sim 1\%$, NONSINGLET $\sim 2 - 3\%$
- DATA REGION: $10 \lesssim M_X \lesssim 3 \cdot 10^3$ TeV, $-4 \lesssim y \lesssim 4$

CONTEMPORARY PDF DETERMINATION: THE NEED FOR THEORETICAL ACCURACY INTRINSIC CHARM

- PERTURBATIVE CHARM ($N_f = 4$) DETERMINED BY MATCHING CONDITIONS
- LARGE HIGHER ORDER CORRECTIONS \Rightarrow N³LO AVAILABLE (Blümlein, Ablinger et al.)
- INTRINSIC CHARM \Rightarrow INVERT MATCHING CONDITIONS
INVERSION \Rightarrow EKO CODE (Candido, Hekhorn, Magni, 2022)

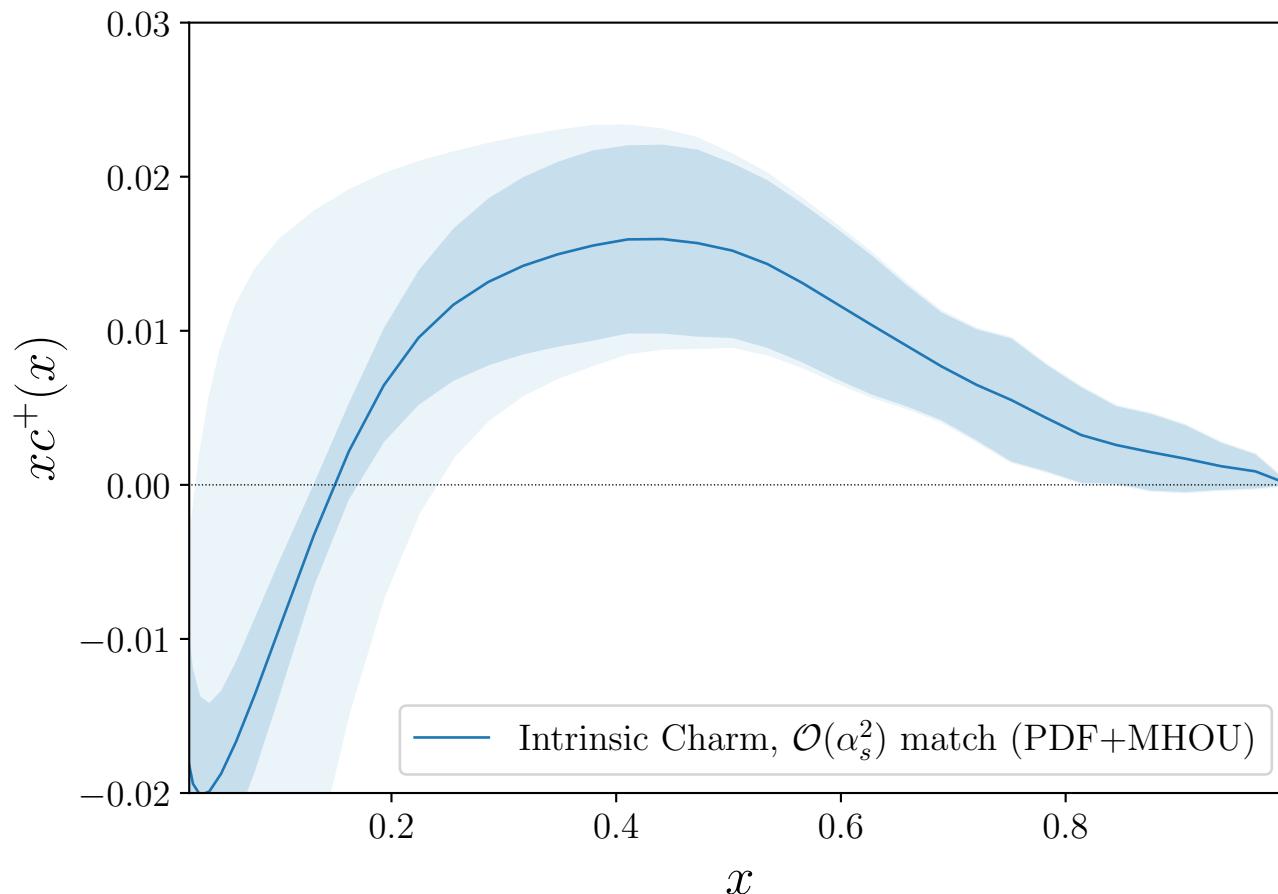
CHARM PDF: $N_f = 4$ vs $N_f = 3$ (NNLO & N³LO CONVERSION)



CONTEMPORARY PDF DETERMINATION

INTRINSIC CHARM!

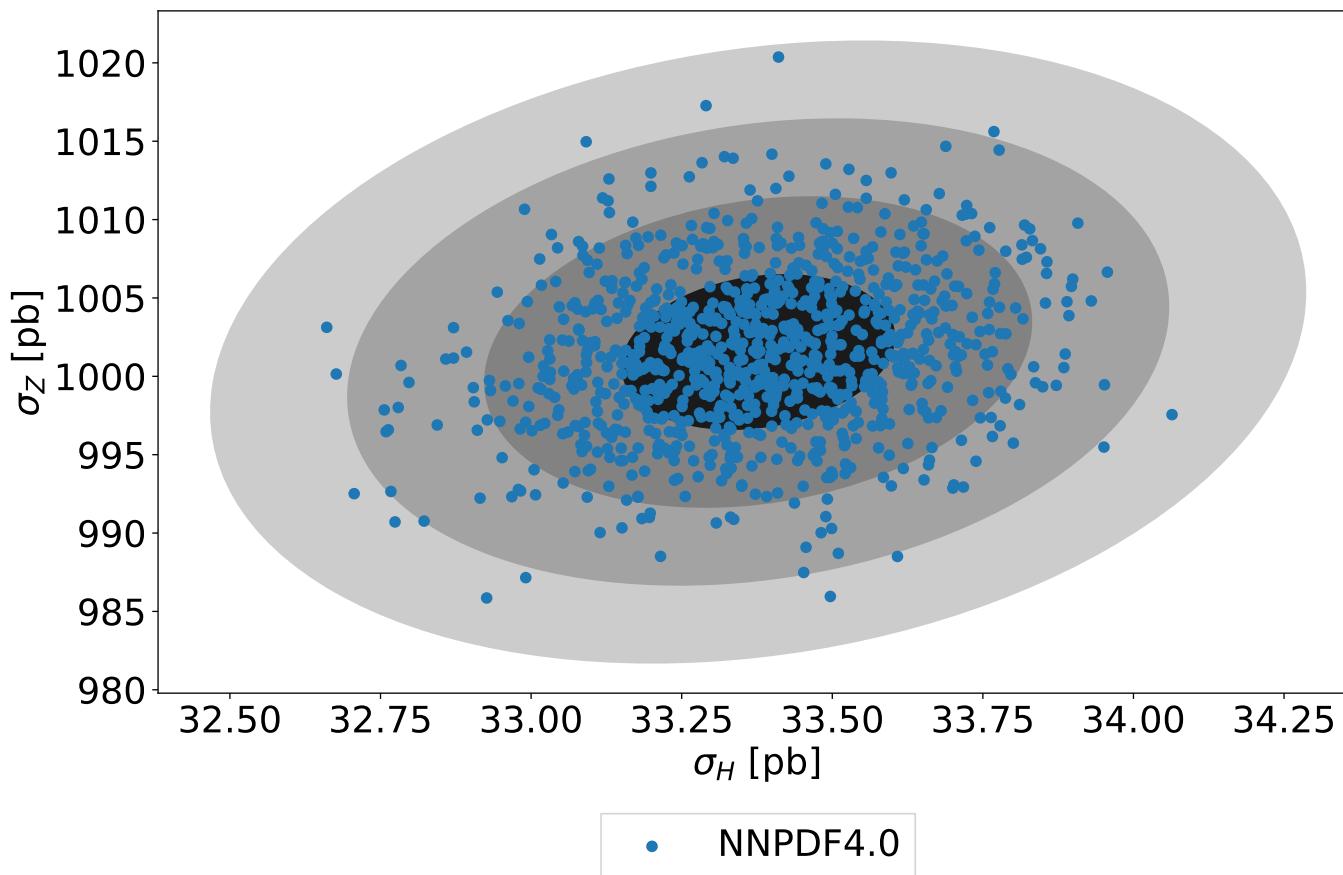
- MHOU ESTIMATED FROM $N^3\text{LO}-\text{NNLO}$ DIFFERENCE
 - LARGE UNCERTAINTY AT SMALL x
 - NEGLIGIBLE UNCERTAINTY IN VALENCE REGION
- COMPATIBLE WITH ZERO AT SMALL x
- CLEAR EVIDENCE FOR INTRINSIC VALENCE PEAK



PDFS AND XAI

CONTEMPORARY PDF DETERMINATION DISTRIBUTION IN FUNCTION SPACE :

- PLOT RESULTS IN (σ_H, σ_Z) PREDICTION SPACE
- DISTRIBUTION OF REPLICAS \Rightarrow IMPORTANCE SAMPLING OF UNDERLYING PROBABILITY

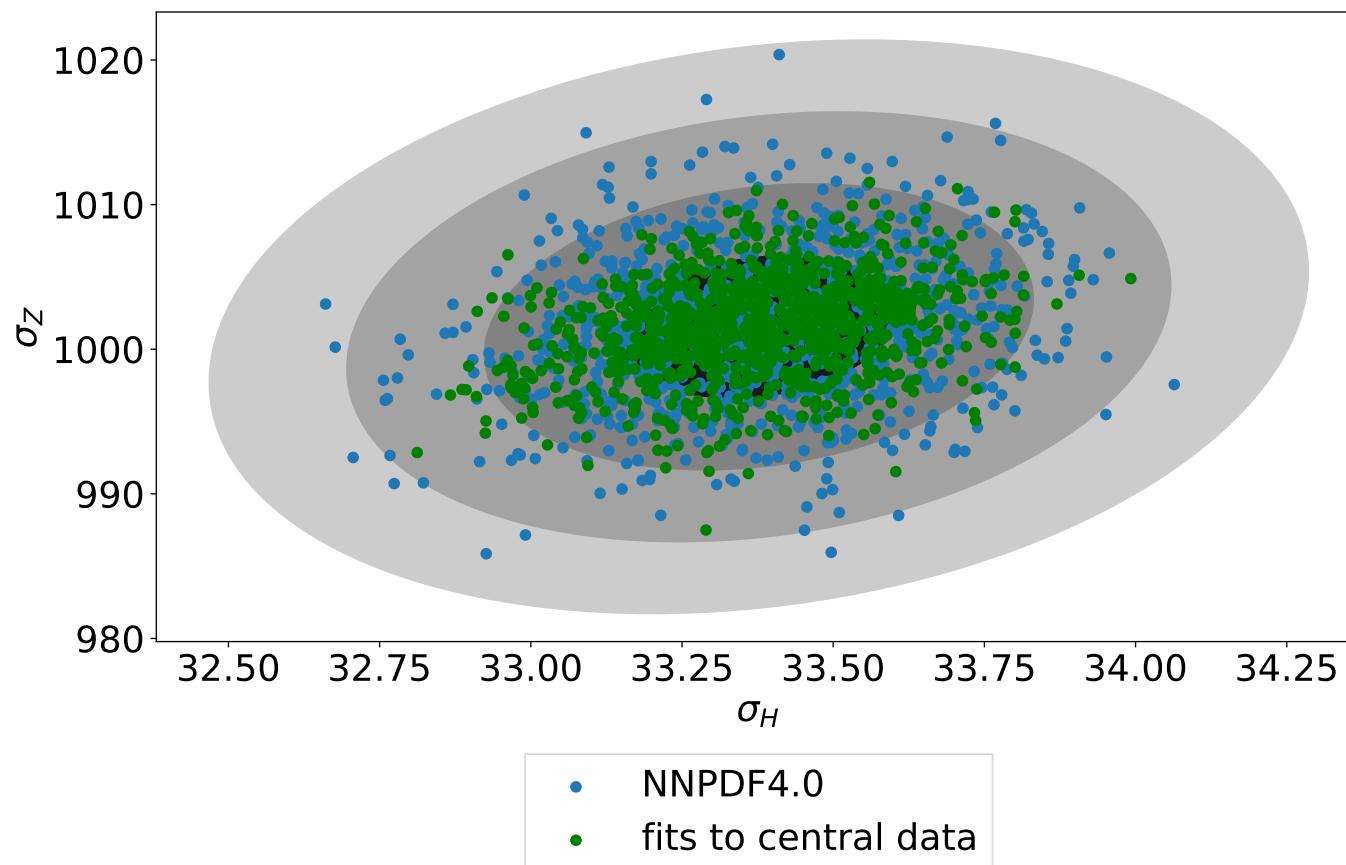


DISTRIBUTION OF REPLICAS DRIVEN BY

- DATA UNCERTAINTIES \Rightarrow DATA REPLICA FLUCTUATION
- INTERPOLATION, EXTRAPOLATION AND FUNCTIONAL UNCERTAINTIES \Rightarrow BEST FIT DEGENERACY

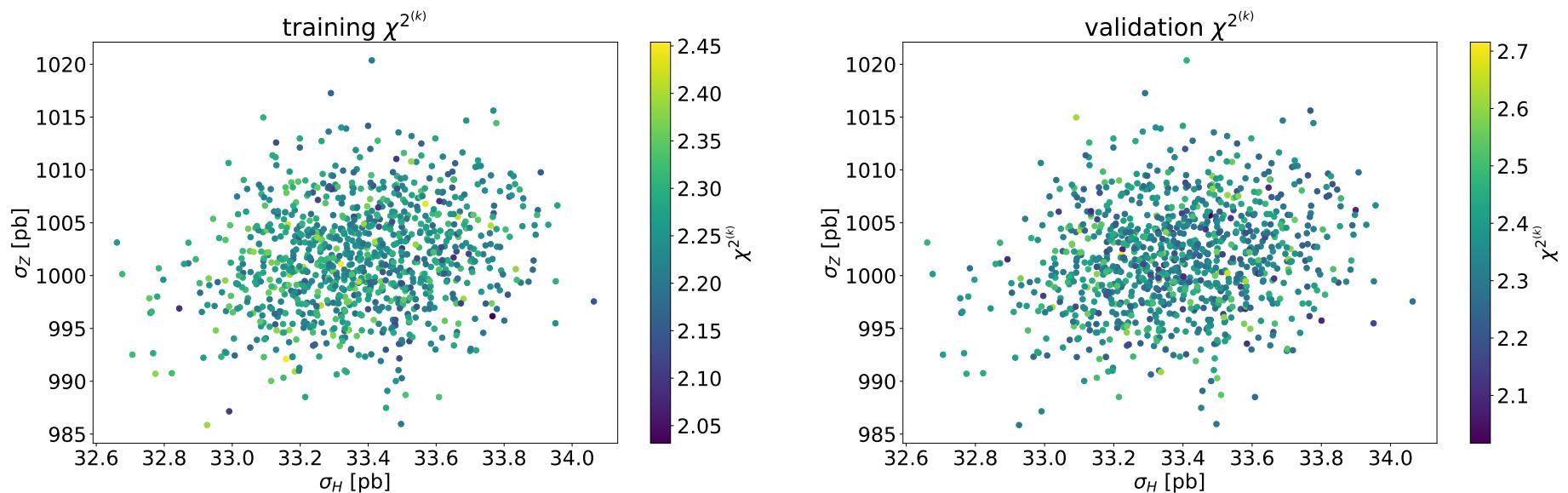
LEVEL-1 VS FULL UNCERTAINTIES

- REPLICA FLUCTUATION \Rightarrow DATA UNCERTAINTIES
- NO REPLICA FLUCTUATION \Rightarrow MODEL UNCERTAINTY



THE REPLICA DISTRIBUTION

LOSS QUALITY

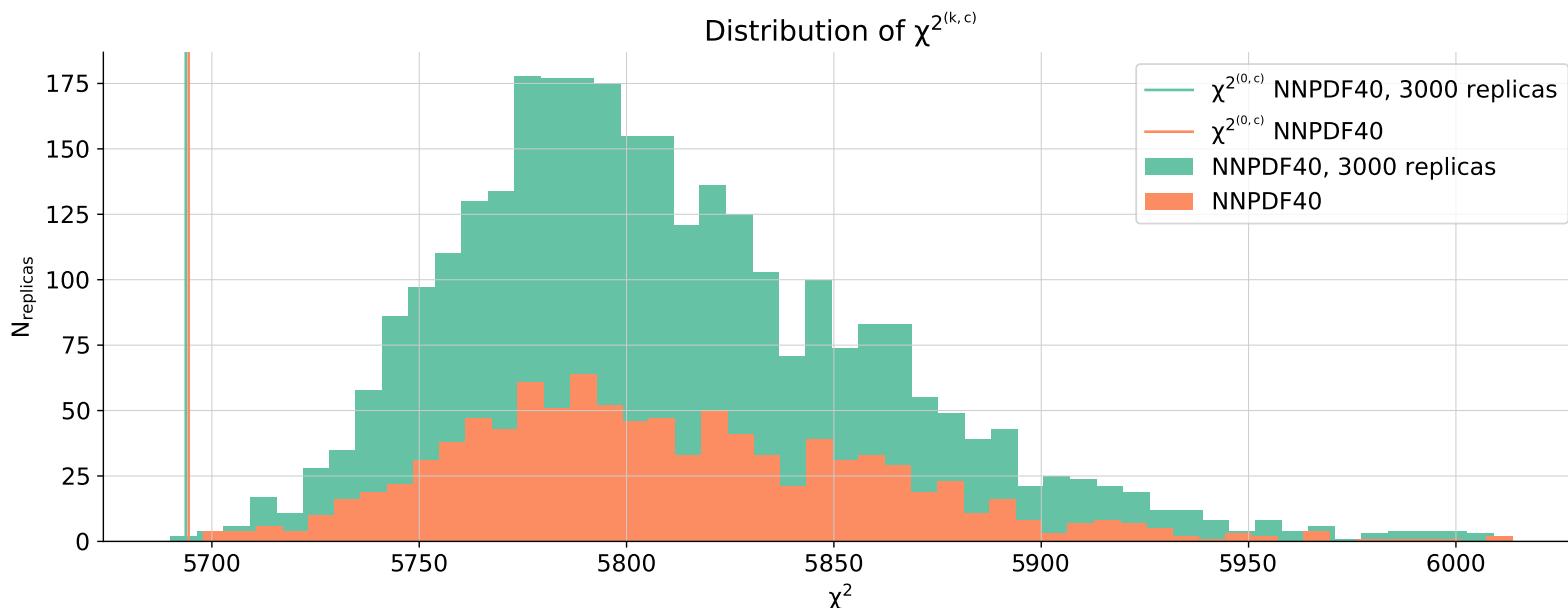


- COMPARE TRAINING AND VALIDATION LOSS FOR EACH REPLICA
- NO CORRELATION BETWEEN FIT QUALITY AND POSITION IN THE (σ_H, σ_Z) PLANE
- UNIFORM QUALITY

CONTEMPORARY PDF DETERMINATION DISTRIBUTION IN FEATURE SPACE LOSS TO CENTRAL DATA

- EACH PDF REPLICA FITTED TO A DATA REPLICA
- LOSS COMPUTED TO CENTRAL DATA STATISTICALLY DISTRIBUTED

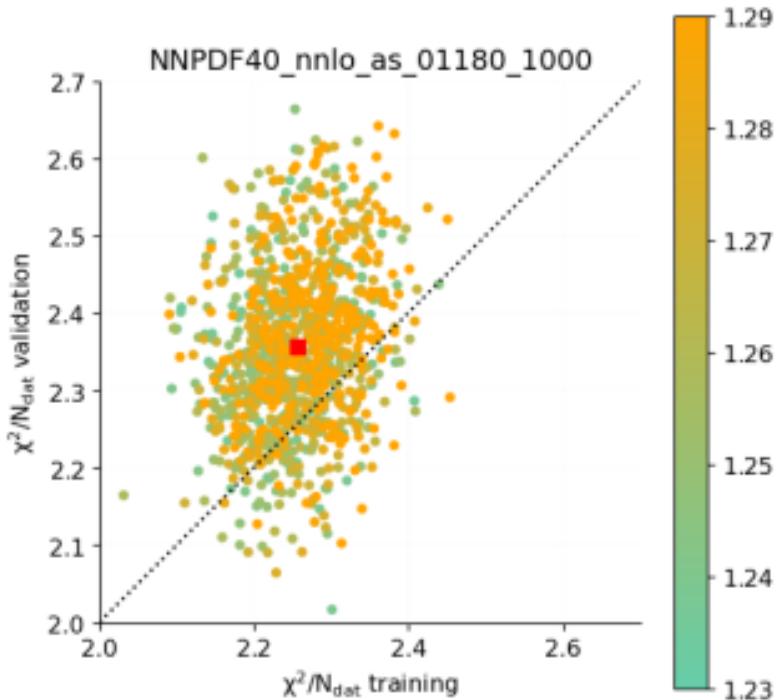
1000 REPLICAS VS. 3000 REPLICAS



- AVERAGE \Rightarrow CENTRAL PREDICTION PDF \Rightarrow LOW LOSS
- NOT NECESSARILY LOWEST

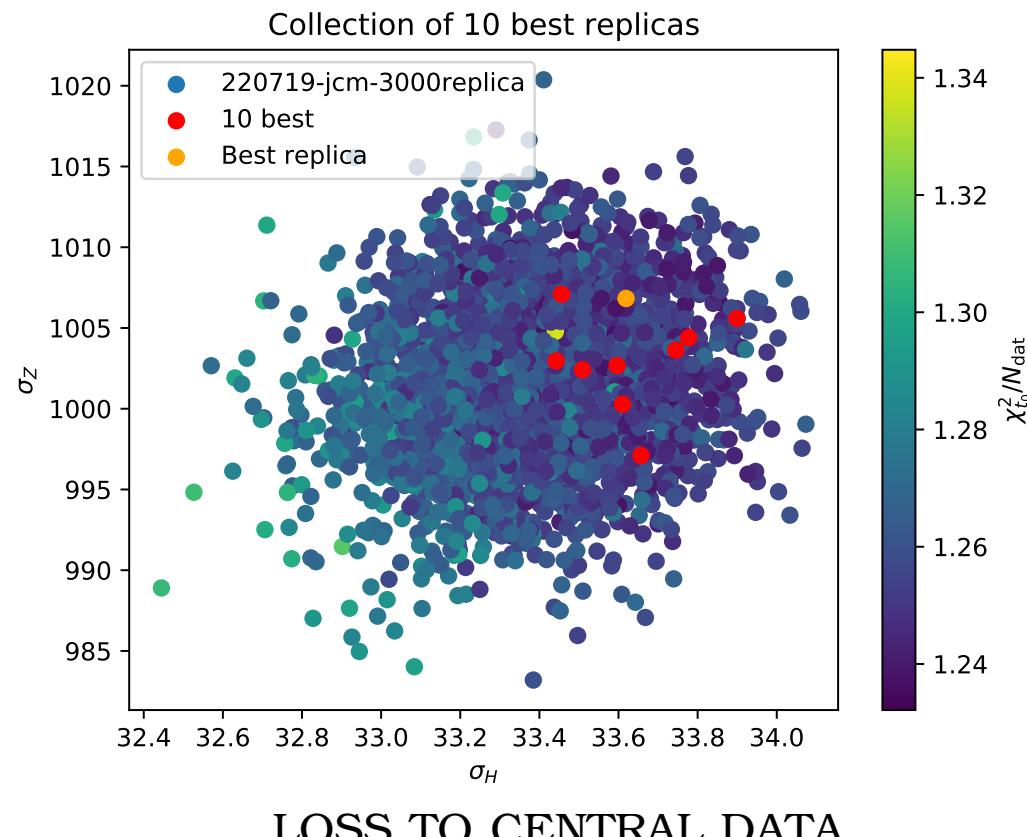
REPLICA LOSS DISTRIBUTION TRAINING AND VALIDATION

- ARE FITS WITH HIGH LOSS TO CENTRAL DATA POOR (UNDERLEARNT)?



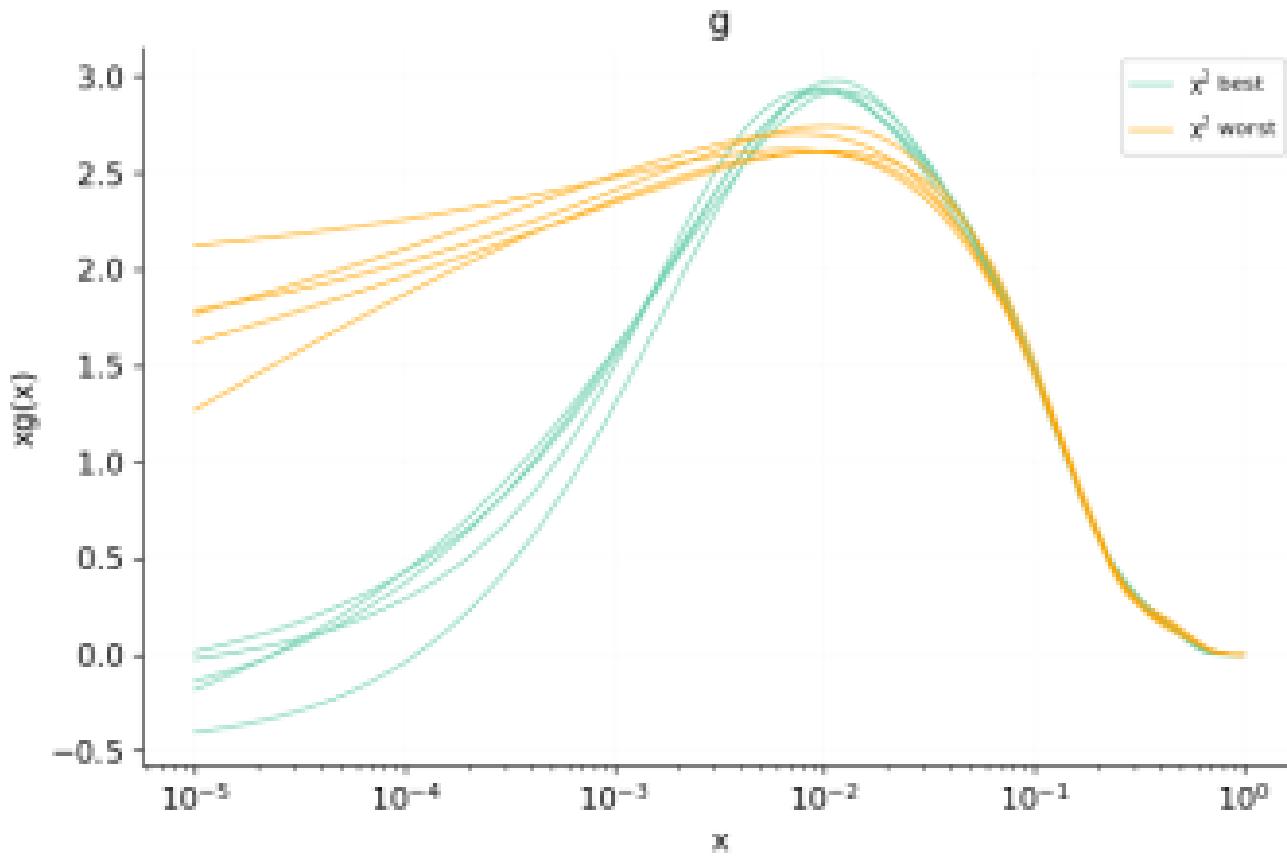
- NO CORRELATION BETWEEN LOSS TO CENTRAL DATA AND TRAINING, VALIDATION LOSS
- UNIFORM FIT QUALITY
- DISPERSION DUE
 - DATA REPLICA FLUCTUATION \Rightarrow DATA UNCERTAINTIES
 - MODEL UNCERTAINTIES
 \Rightarrow INTERPOLATION, EXTRAPOLATION AND FUNCTIONAL UNCERTAINTIES

FEATURE SPACE VS. FUNCTION SPACE: CORRELATION



- CORRELATED TO POSITION IN (σ_H, σ_z) PLANE
- CORRELATED TO A FEATURE?

FEATURE SPACE VS. FUNCTION SPACE:
REPLICAS WITH LOWEST & HIGHEST LOSS TO CENTRAL DATA
THE GLUON



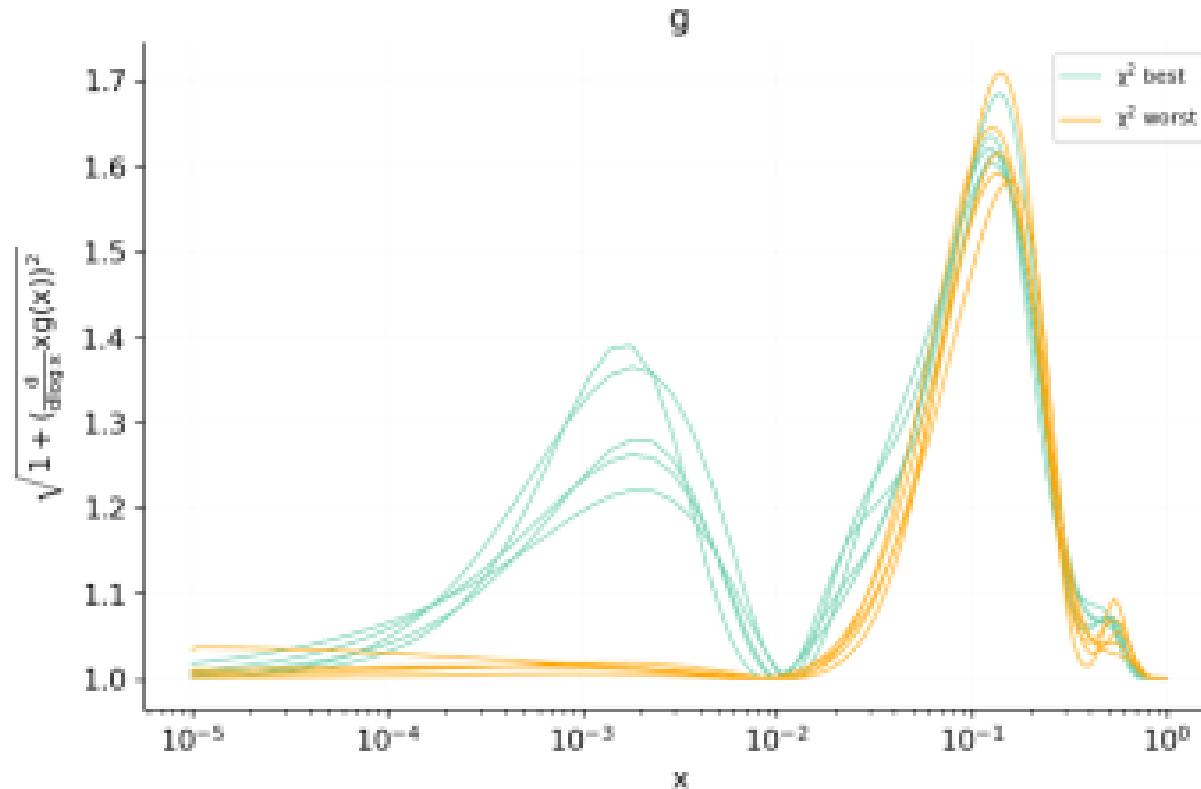
- REPLICAS CLOSER TO CENTRAL DATA \Rightarrow MORE STRUCTURE

THE PDF KINETIC ENERGY

REPLICAS WITH LOWEST & HIGHEST LOSS TO CENTRAL DATA

$$KE = \sqrt{1 + \left(\frac{d}{d \ln x} x f(x, Q^2) \right)^2}$$

ARCLENGTH OF THE NN OUTPUT IN TERMS OF INPUT
THE GLUON

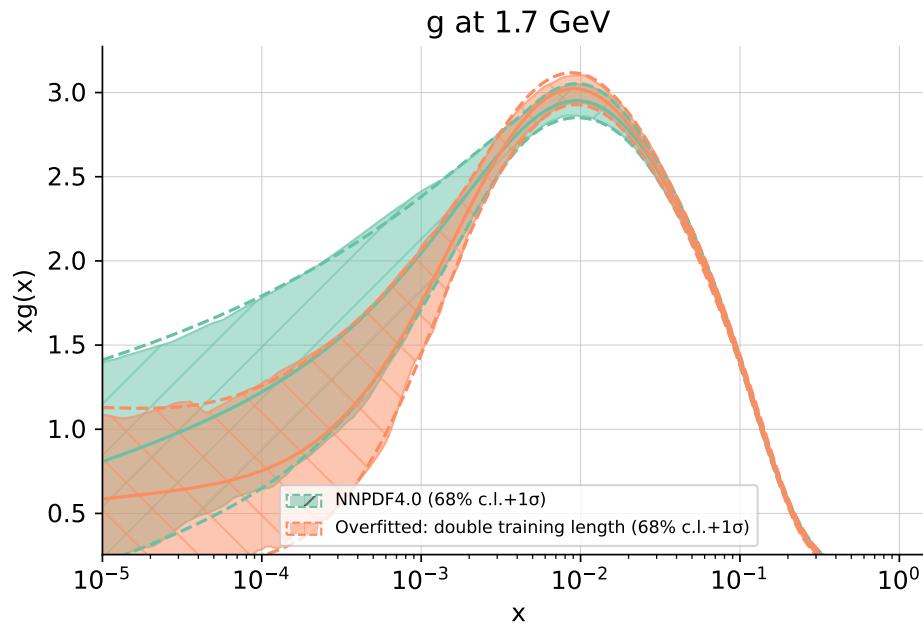


- REPLICAS **CLOSER** TO CENTRAL DATA \Rightarrow **MORE STRUCTURE**
- **HIGHER KINETIC ENERGY**

OVERLEARNING FEATURES

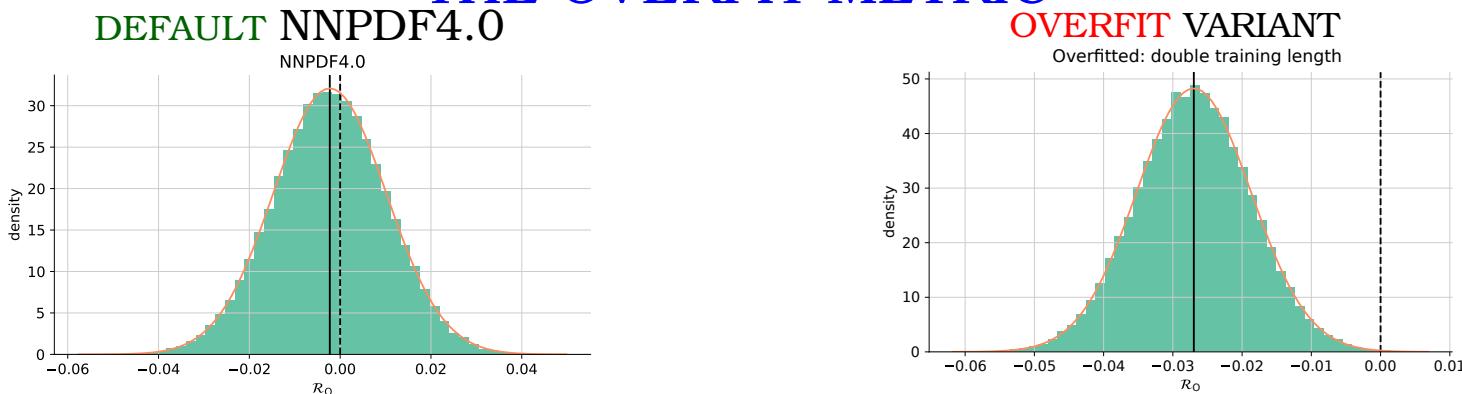
- INDUCE OVERLEARNING: DOUBLE TRAINING LENGTH

THE GLUON



- LOOK AT THE OUTPUT \Rightarrow MORE STRUCTURE IN GLUON

THE OVERFIT METRIC

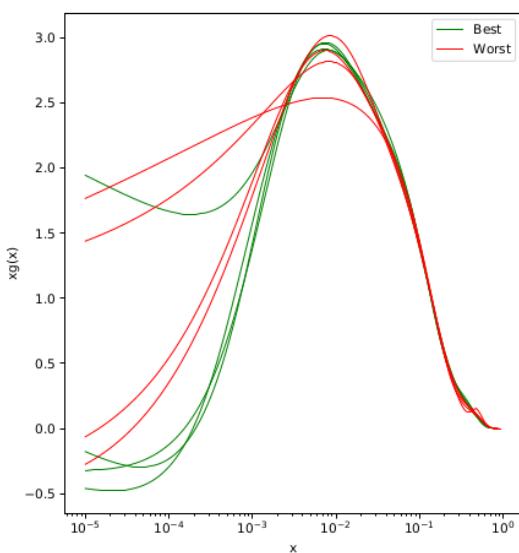


EXPLANATION GENERALIZATION

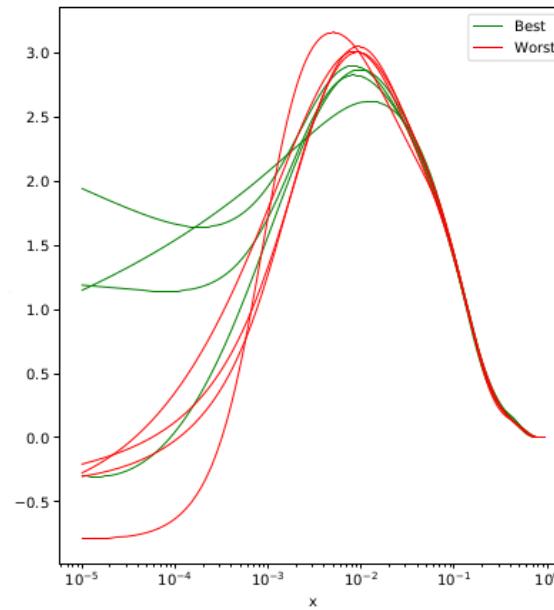
- OVERFITTING \Rightarrow POOR GENERALIZATION
- KEPT IN CHECK BY K-FOLDING (NOT CROSS-VALIDATION)
- LOOK AT BEST LOSS TO FITTED VS. EXCLUDED FOLDS

THE GLUON

FITTED FOLDS



EXCLUDED FOLD

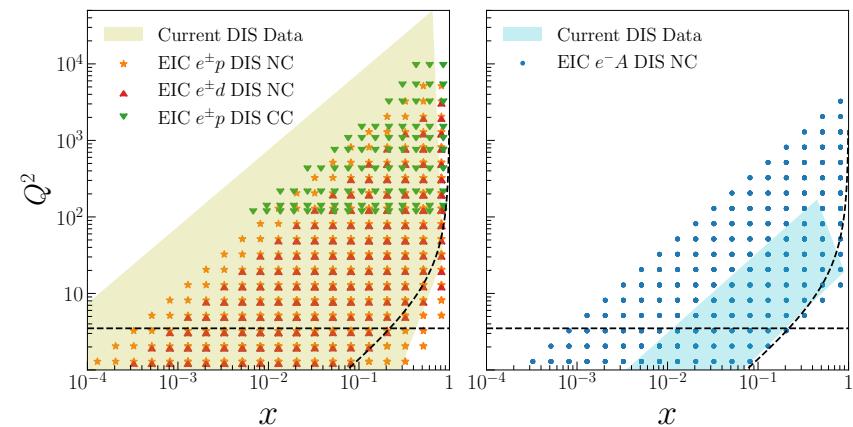
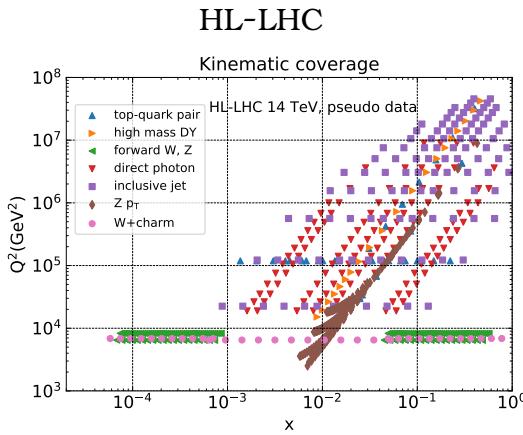


- BEST VS WORST REVERSED
- HIGH K.E. SOLUTIONS DO NOT GENERALIZE

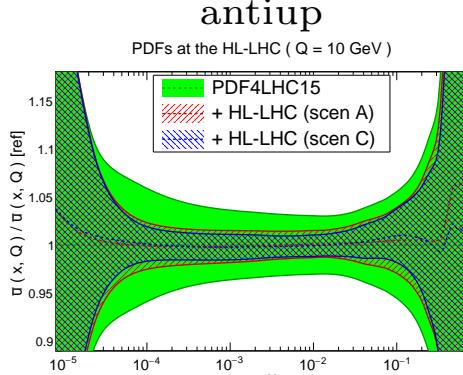
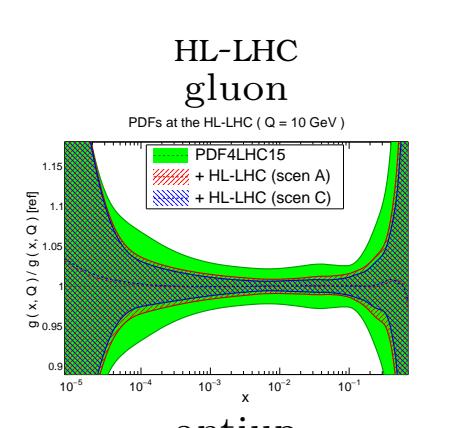
THE ERA OF THE EIC

THE IMPACT OF THE EIC: KINEMATIC COVERAGE

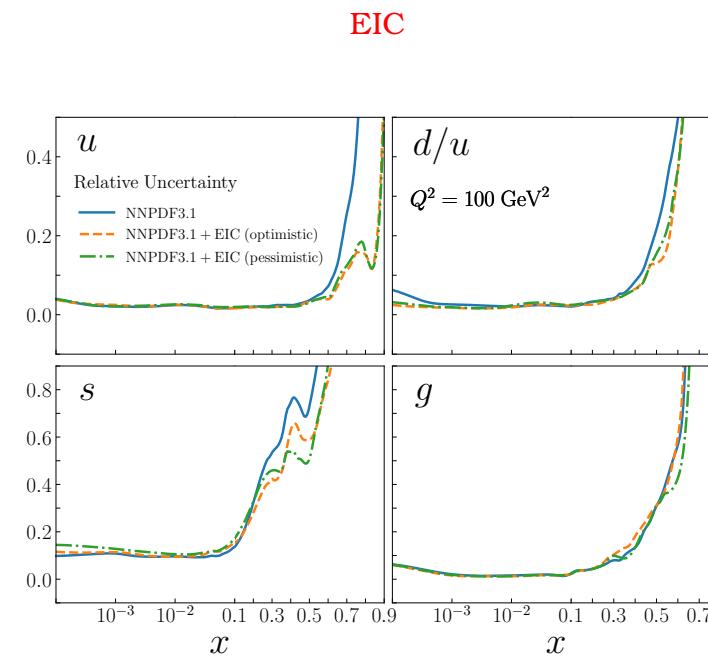
EIC



- COMPLEMENTARY KINEMATICS AND INFORMATION COMPARED TO HL-LHC
- LARGE x KINEMATICS, POLARIZATION, NUCLEAR



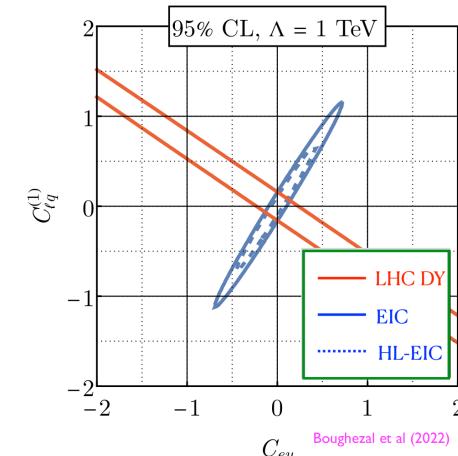
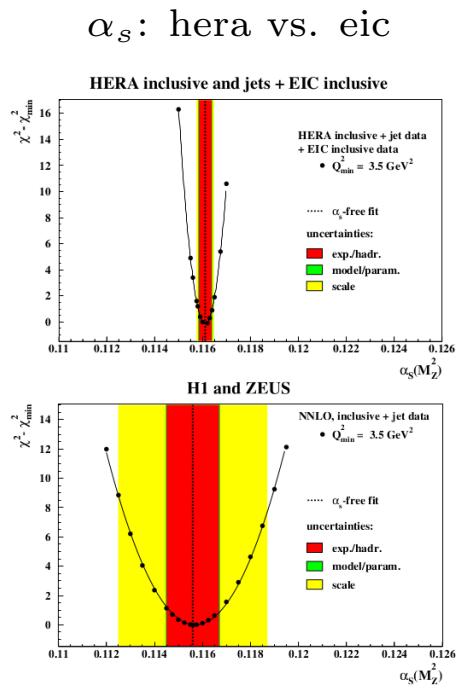
PDFs



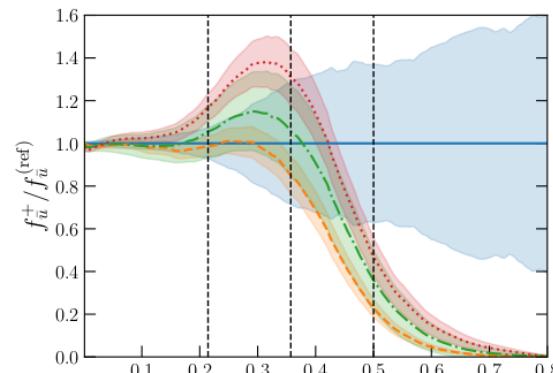
THE IMPACT OF THE EIC

SMEFT:
 $\bar{e}\gamma^\mu e \bar{u}\gamma_\mu u, \bar{l}\gamma^\mu l \bar{q}\gamma_\mu q$ plane

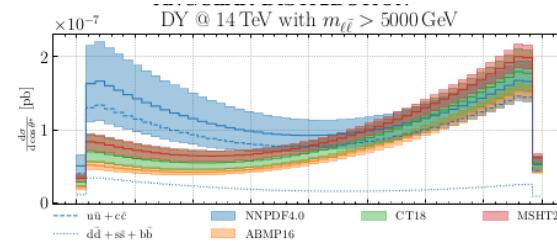
- **SMEFT FITS:** RESOLVING DEGENERACIES (Boughezal et al., 2021-2023)
- α_s DETERMINATION AND PDFS (Cerci et al., 2023)
- **LARGE x PDFS AND HIGH-MASS STATES** (NNPDF, 2022)



large x PDFS: antiup



DY forward-backward asym



EIC AND MACHINE LEARNING

Artificial Intelligence for the Electron Ion Collider (AI4EIC)

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- PDFs: COLLINEAR AND GPDs
- MONTE CARLO EVENT GENERATORS
- DETECTOR SIMULATION
- CROSS-SECTION INFERENCE
- EVENT RECONSTRUCTION AND PARTICLE IDENTIFICATION
- HARDWARE ACCELERATION
- STREAMING READOUT DATA AQUISITION

CONCLUSION

**NO EFFECT THAT REQUIRES MORE THAN 10% ACCURACY IN
MEASUREMENT IS WORTH INVESTIGATING**

Walther Nernst

~~NO EFFECT THAT REQUIRES MORE THAN 10% ACCURACY IN
MEASUREMENT IS WORTH INVESTIGATING~~
Walther Nernst

ACCURACY OF OBSERVATION IS THE EQUIVALENT OF
ACCURACY OF THINKING
Wallace Stevens