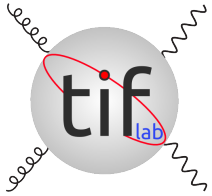
MACHINE LEARNING PDFs

STEFANO FORTE
UNIVERSITÀ DI MILANO & INFN

UNIVERSITÀ DEGLI STUDI DI MILANO
DIPARTIMENTO DI FISICA



XXVII EPIPHANY CONFERENCE

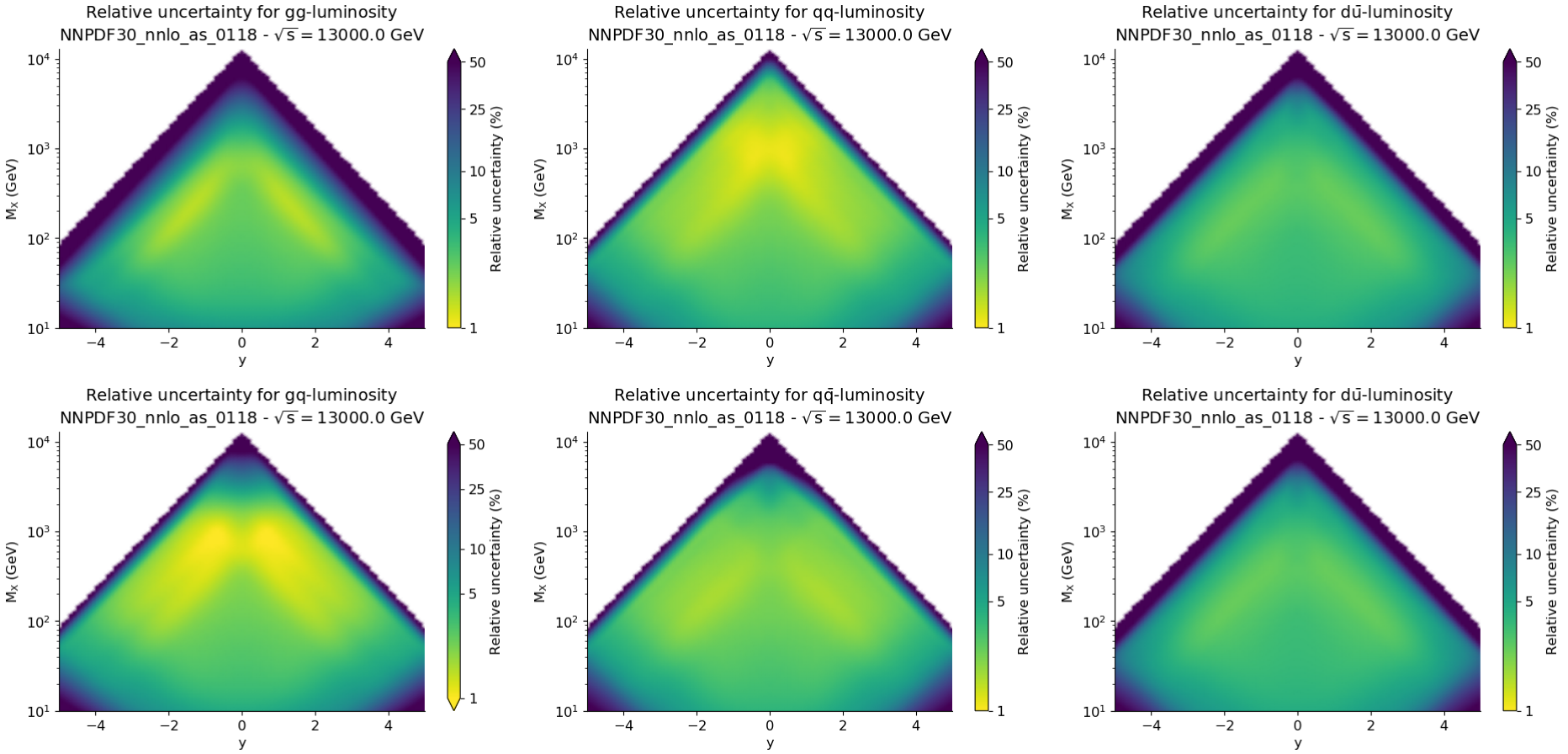
CRACOW, JANUARY 7, 2020

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 740006

MOTIVATIONS I: ACCURACY

PDF4LHC PDFs (2014) NNPDF3.0 NNLO

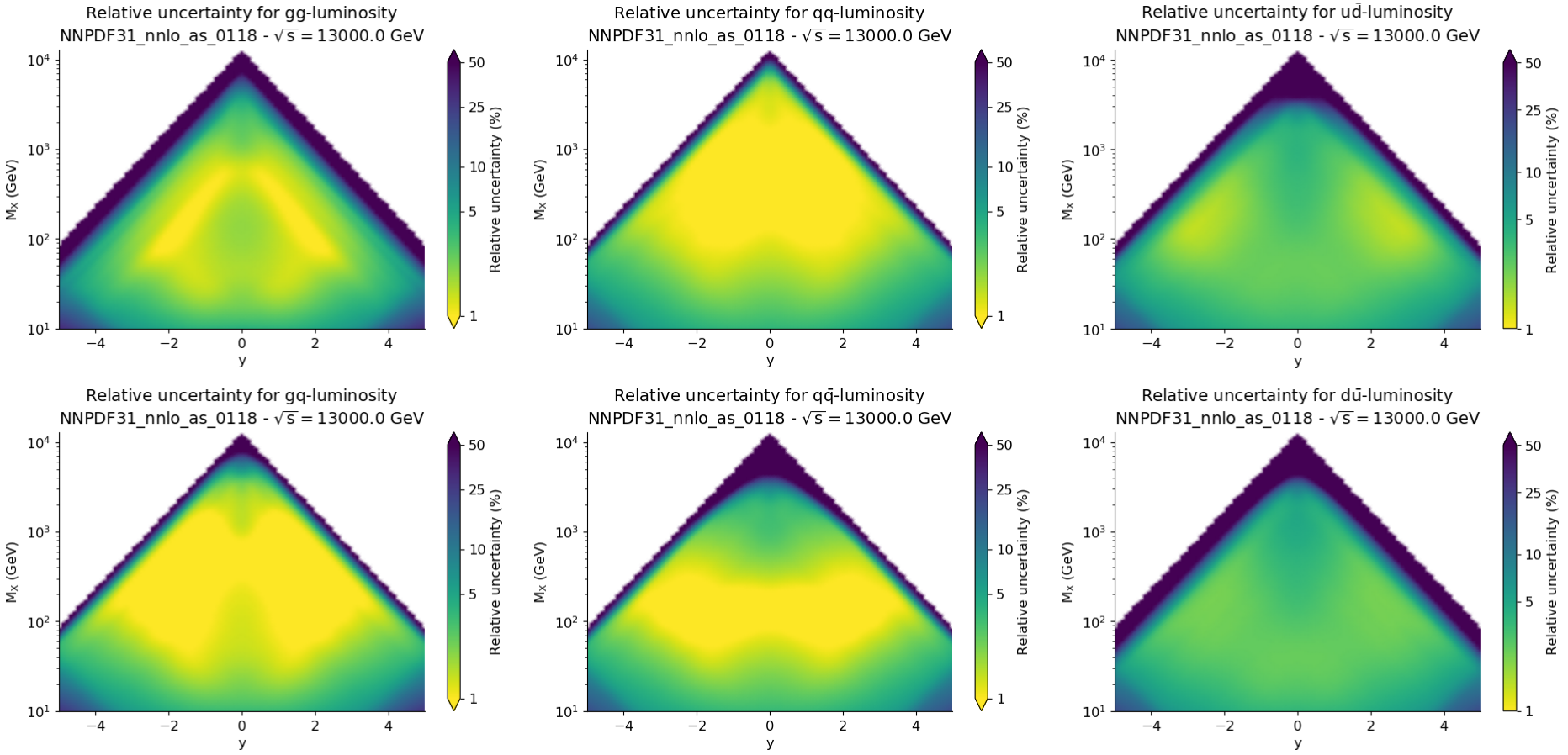
GLUON SINGLET FLAVORS



- GLUON BETTER KNOWN AT SMALL x, VALENCE QUARKS AT LARGE x, SEA QUARKS IN BETWEEN
- TYPICAL UNCERTAINTIES IN DATA REGION $\sim 3 - 5\%$
- SWEET SPOT: VALENCE Q - G; DOWN TO 1%
- UP BETTER KNOWN THAN DOWN; FLAVOR SINGLET BETTER THAN INDIVIDUAL FLAVORS

MOTIVATIONS I: ACCURACY
CURRENT PDFs (2017) NNPDF3.1 NNLO

GLUON SINGLET FLAVORS

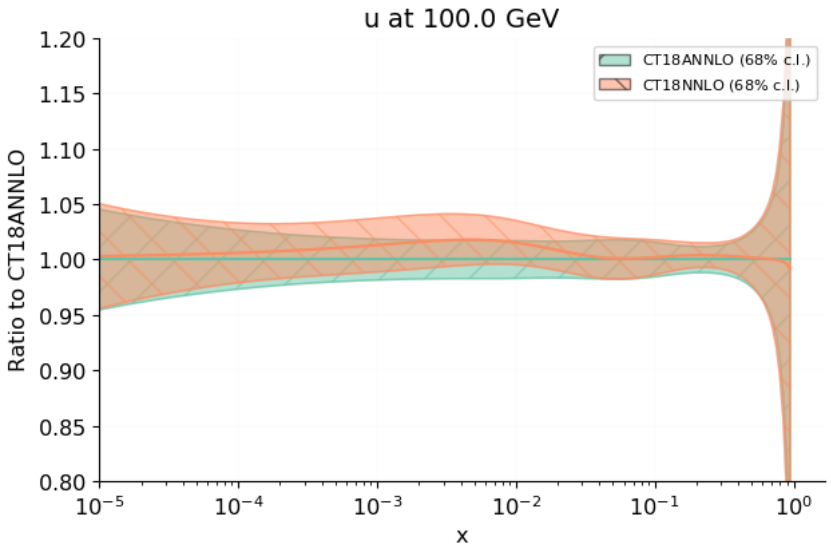


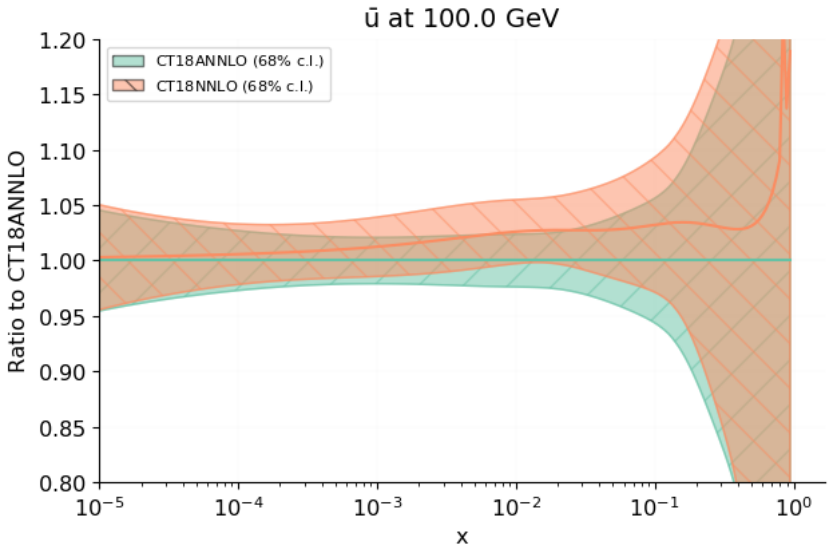
- GLUON BETTER KNOWN AT SMALL x, VALENCE QUARKS AT LARGE x, SEA QUARKS IN BETWEEN
- TYPICAL UNCERTAINTIES IN DATA REGION $\sim 1-3\%$
- SWEET SPOT: VALENCE Q - G; 1% OR BELOW
- UP BETTER KNOWN THAN DOWN; FLAVOR SINGLET BETTER THAN INDIVIDUAL FLAVORS

MOTIVATIONS II: CONSISTENCY

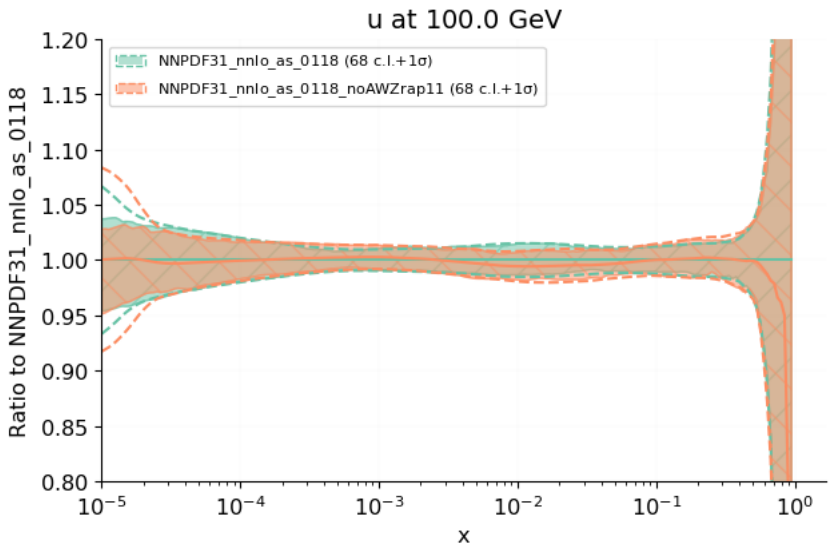
IMPACT OF ATLAS W/Z 7TEV DATA

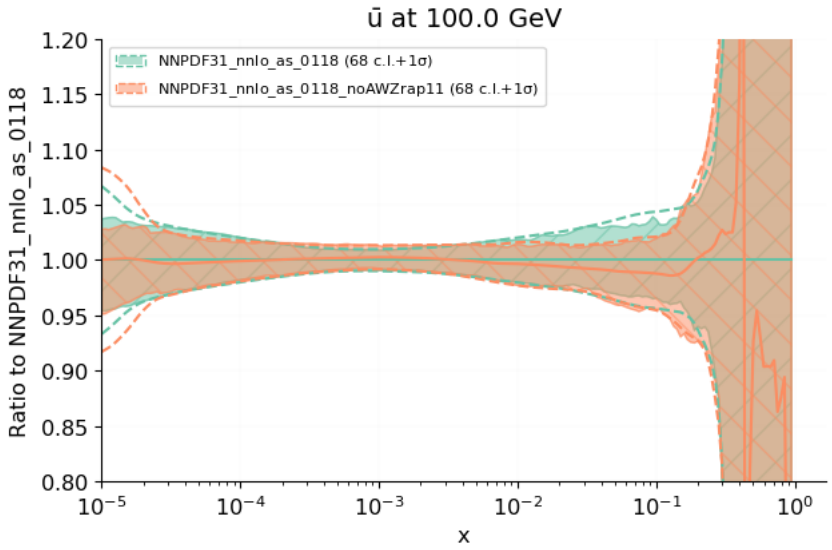
CT18





NNPDF3.1



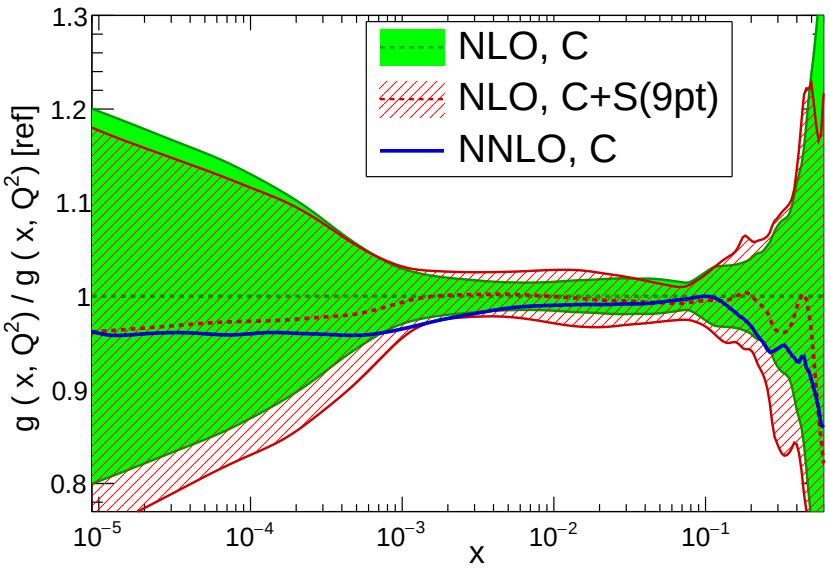


- CT18: PDF SETS RELEASED WITH/WITHOUT ATLAS W/Z DATA INCLUDED
- NNPDF3.1: CONSISTENCY OF ALL DATASETS INCLUDED

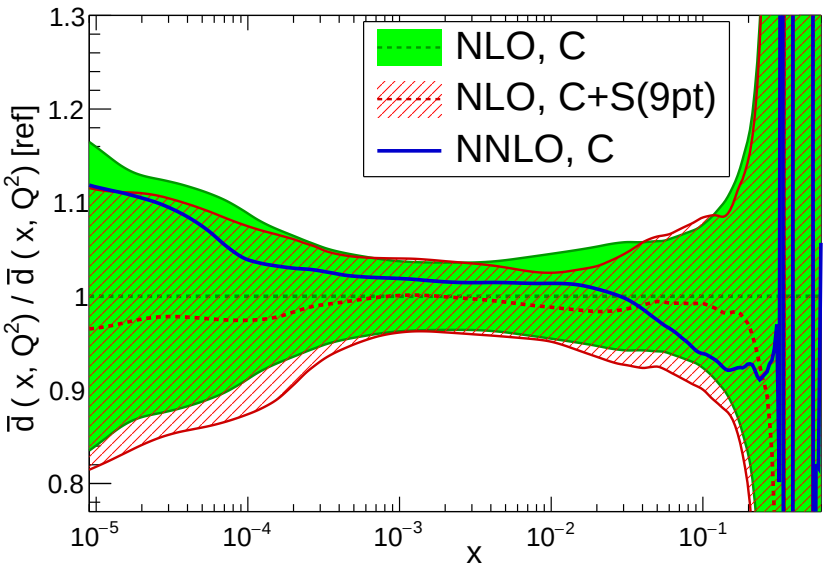
MOTIVATIONS III: ACCURACY

PDFs WITH THEORY UNCERTAINTIES

GLUON



ANTIDOWN

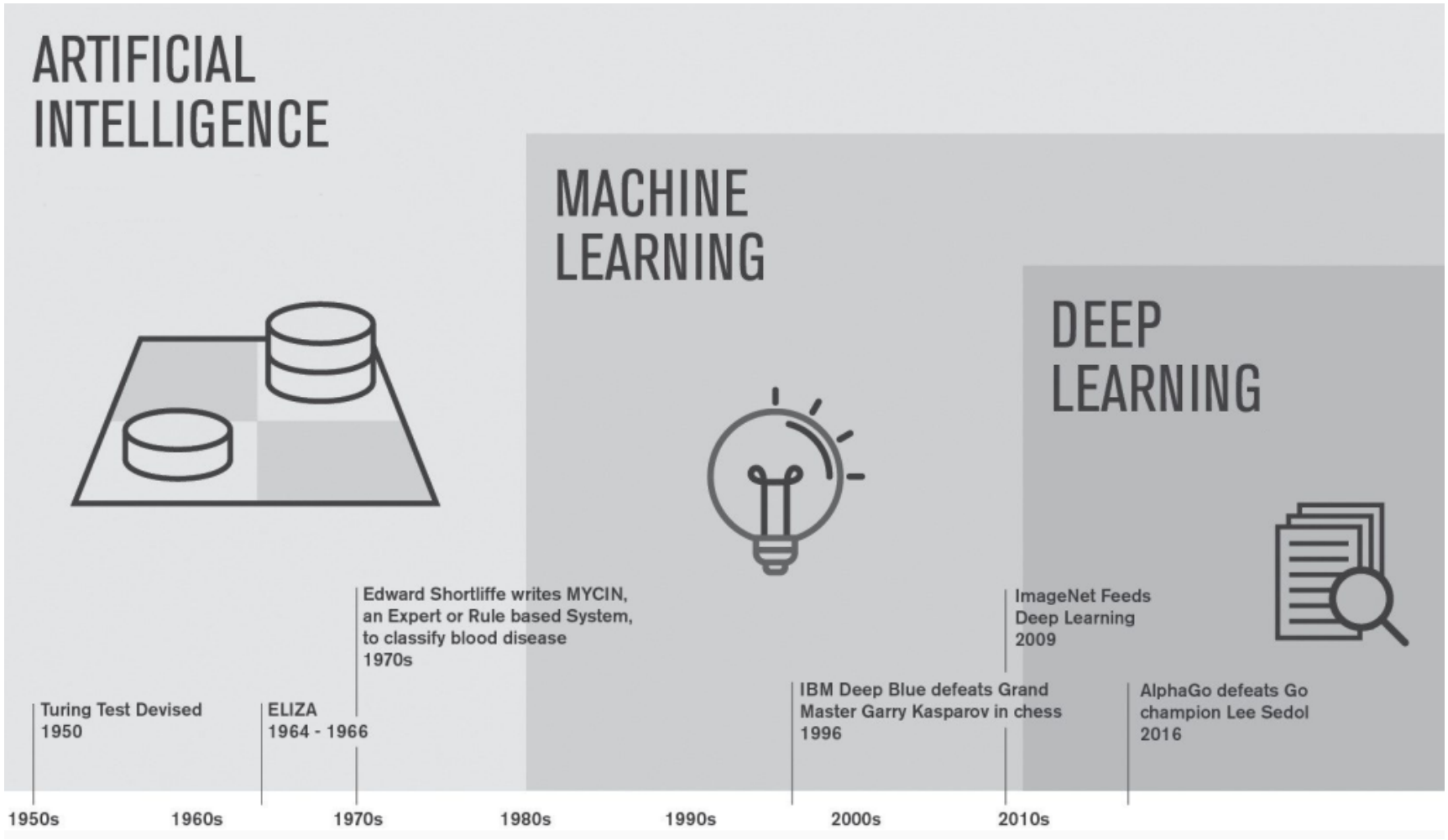


	C	$C + S^{(9\mathrm{pt})}$
χ^2	1.139	1.109
ϕ	0.314	0.415

- FIT QUALITY χ^2 IMPROVES
- RELATIVE ERROR ϕ ON PREDICTION MILDLY INCREASED
- CENTRAL VALUE MOVES TOWARDS KNOWN NNLO

EQUALLY PRECISE BUT MORE ACCURATE RESULT!

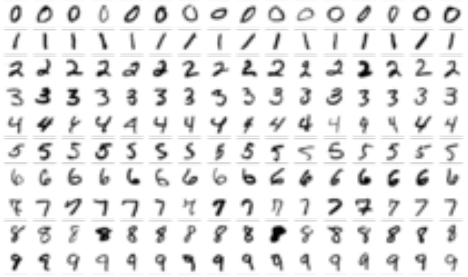
THE WAY AHEAD



ARTIFICIAL INTELLIGENCE: PARADIGMS

"KNOWLEDGE BASED" AI

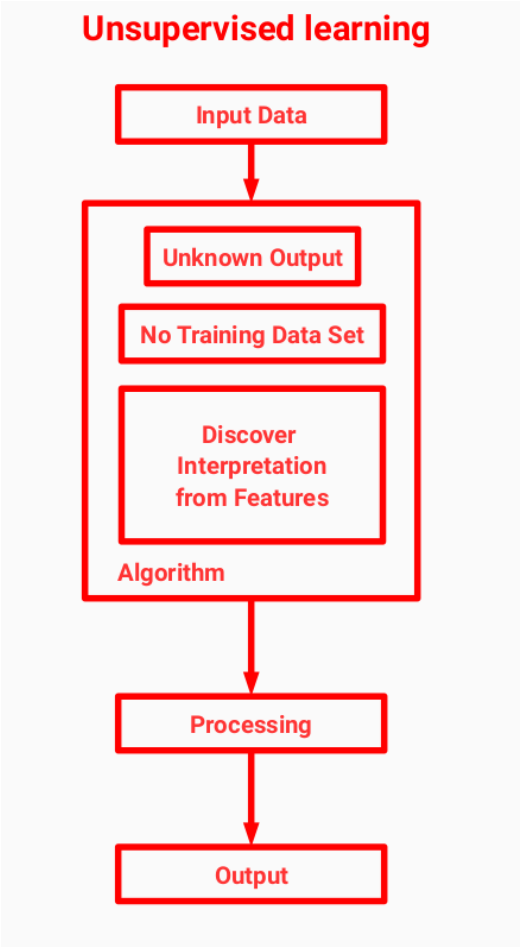
- LEARN AND IMPLEMENT A SET OF RULES
- GOOD FOR CHESS, BAD FOR REAL LIFE



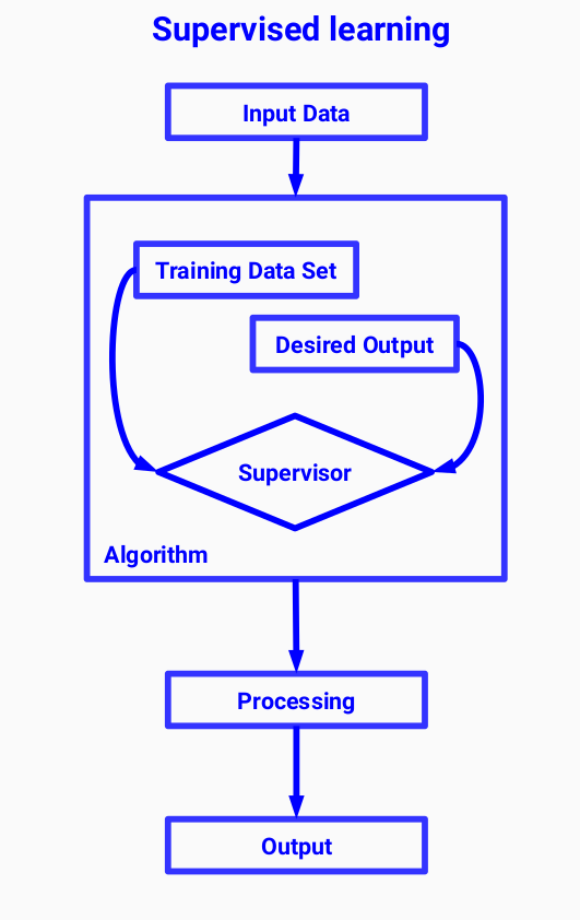
MACHINE LEARNING

- "INTUITIVE" REPRESENTATION
- THE AI AGENT BUILID UP ITS OWN KNOWLEDGE

ARTIFICIAL INTELLIGENCE: ALGORITHMS



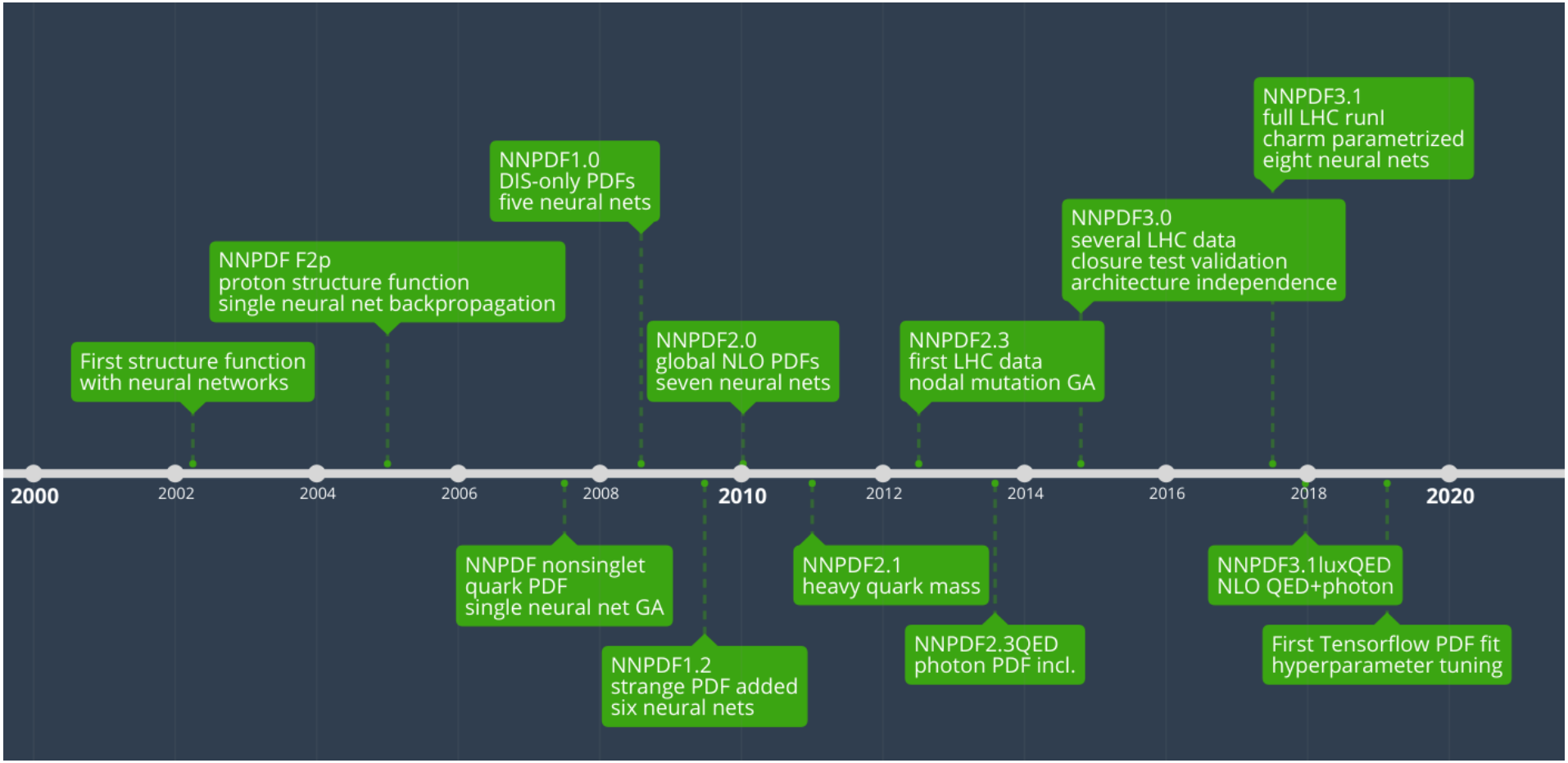
EXTRACT AND OPTIMIZE
DATA FEATURES



OPTIMIZE A PROPERTY
LEARNING FROM DATA

LEARN FROM DATA
THE LEARNING STRATEGY

PROTON STRUCTURE AS AN AI PROBLEM:
NNPDF



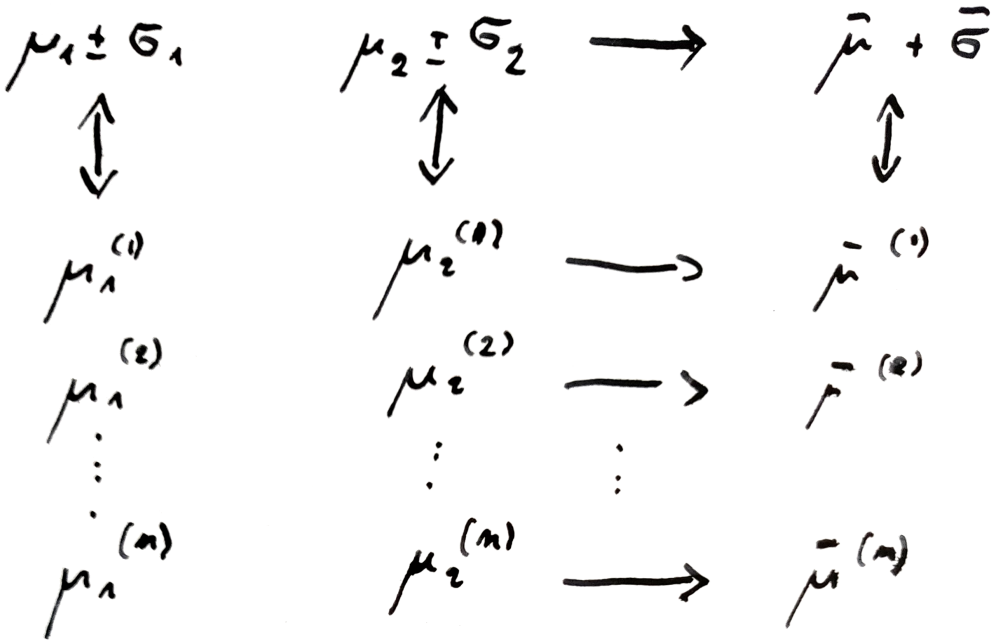
MONTECARLO + NEURAL NETWORKS

THE NNPDF APPROACH
COMBINING DATA BY MONTE CARLO

TWO MEASUREMENTS: $\mu_1 \pm \sigma_1$; $\mu_2 \pm \sigma_2$

MC COMBINATION: $\bar{\mu} \pm \bar{\sigma}$; $\bar{\mu} = \frac{\frac{\mu_1}{\sigma_1^2}+\frac{\mu_2}{\sigma_2^2}}{\frac{1}{\sigma_1^2}+\frac{1}{\sigma_2^2}}$; $\bar{\sigma}^2 = \frac{1}{\frac{1}{\sigma_1^2}+\frac{1}{\sigma_2^2}}$

MONTE CARLO REPRESENTATION



$\mu^{(i)} \Leftrightarrow$ REPLICA SAMPLE $\Leftrightarrow$ REPRESENTATION OF PROBABILITY DISTRIBUTION

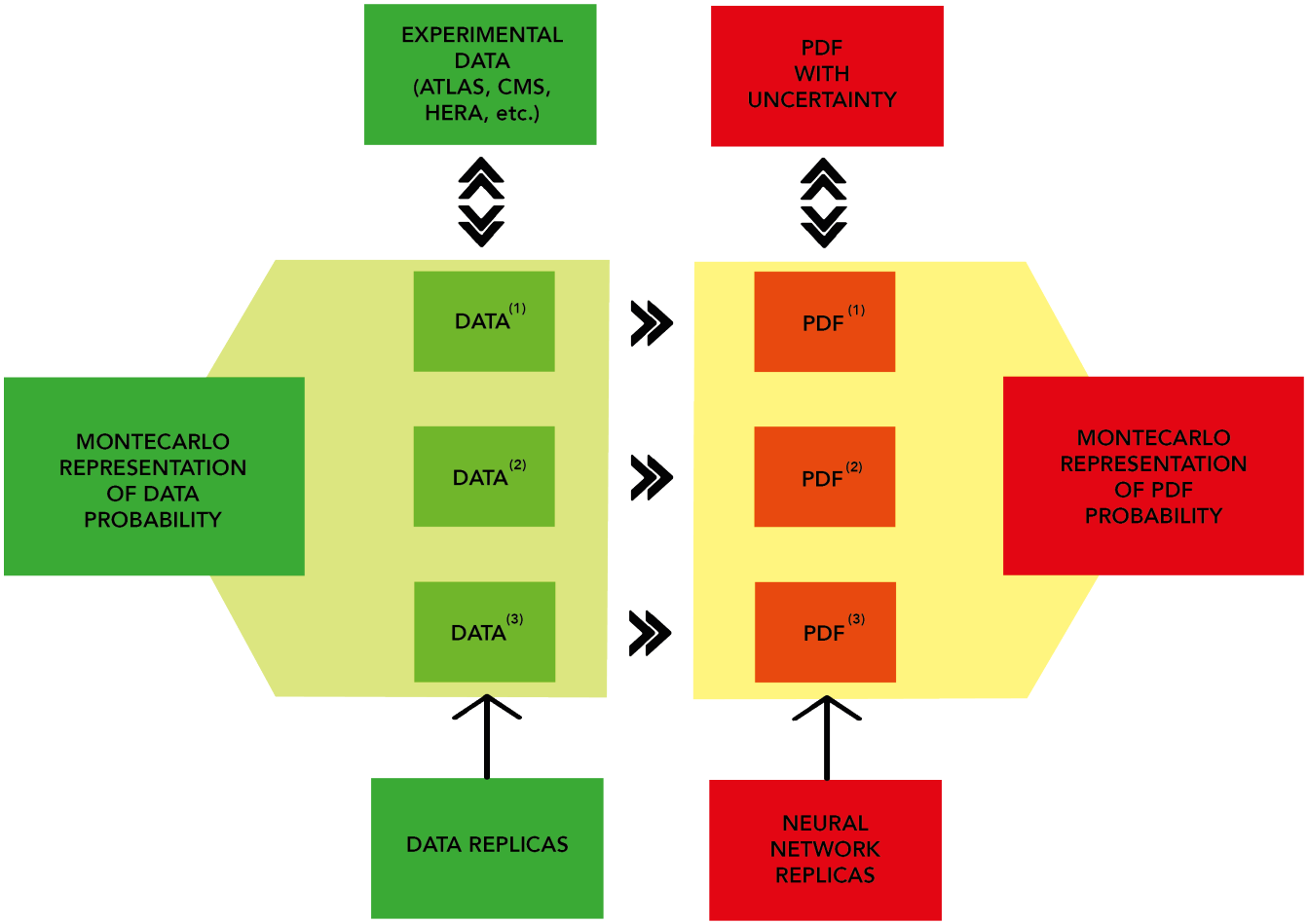
NEED ONLY TO KNOW HOW TO COMBINE CENTRAL VALUES

THE NNPDF APPROACH

THE FUNCTIONAL MONTE CARLO

REPLICA SAMPLE OF FUNCTIONS $\Leftrightarrow$ PROBABILITY DENSITY IN FUNCTION SPACE

KNOWLEDGE OF FUNCTIONAL FORM NOT NECESSARY



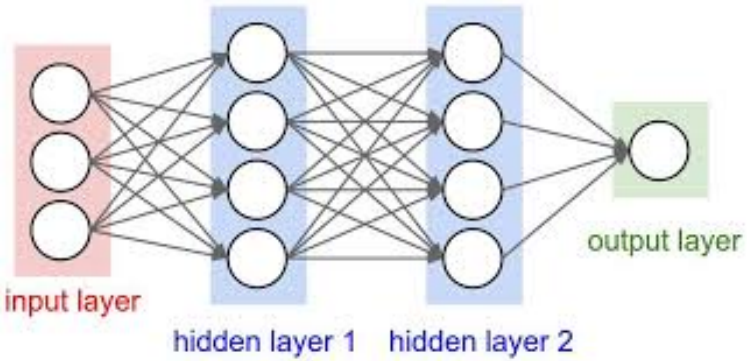
FINAL PDF SET: $f_i^{(a)}(x,\mu)$;

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

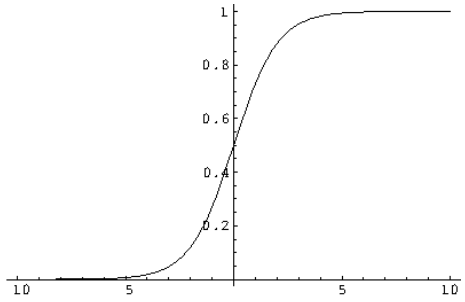
ARTIFICIAL INTELLIGENCE

NEURAL NETWORKS

ARCHITECTURE



ACTIVATION FUNCTION



PARAMETERS

- WEIGHTS ω_{ij}
- THRESHOLDS θ_i

$$F^{(i)}_{\rm out}(\vec{x}_{\rm in}) = F\left(\sum_j \omega_{ij} x^j_{\rm in} - \theta_i\right)$$

SIMPLEST EXAMPLE

1-2-1

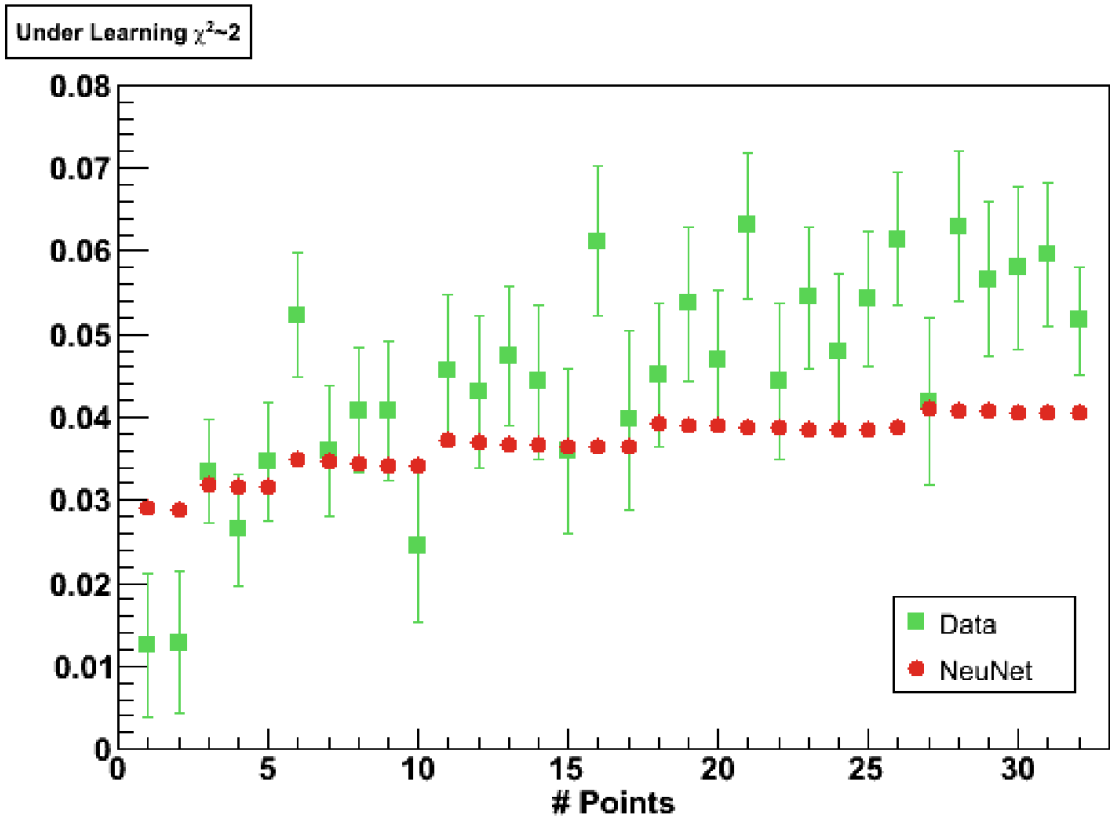
$$f(x) = \frac{1}{1+e^{\theta_1^{(3)} - \frac{\omega_{11}^{(2)}}{1+e^{\theta_1^{(2)} - x\omega_{11}^{(1)}}} - \frac{\omega_{12}^{(2)}}{1+e^{\theta_2^{(2)} - x\omega_{21}^{(1)}}}}}$$

NNPDF: $2-5-3-1$ NN FOR EACH PDF: $37 \times 8 = 296$ PARAMETERS

NEURAL LEARNING

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

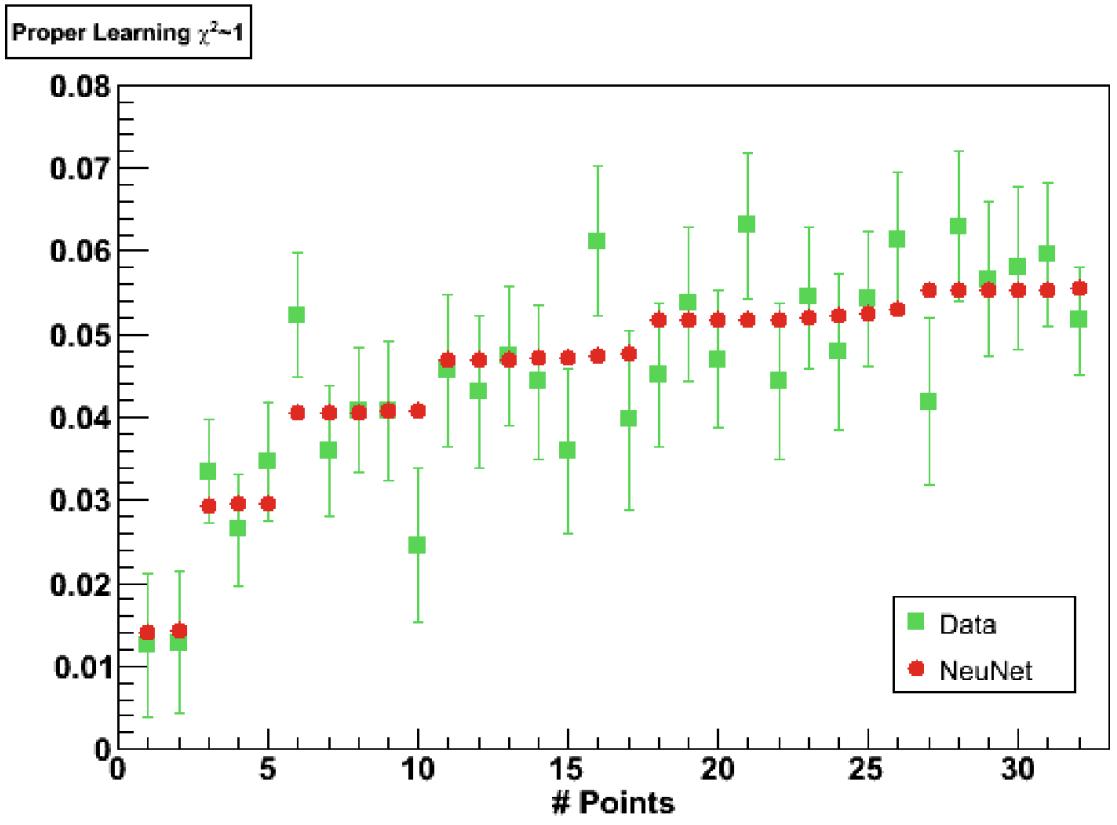
UNDERLEARNING



NEURAL LEARNING

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

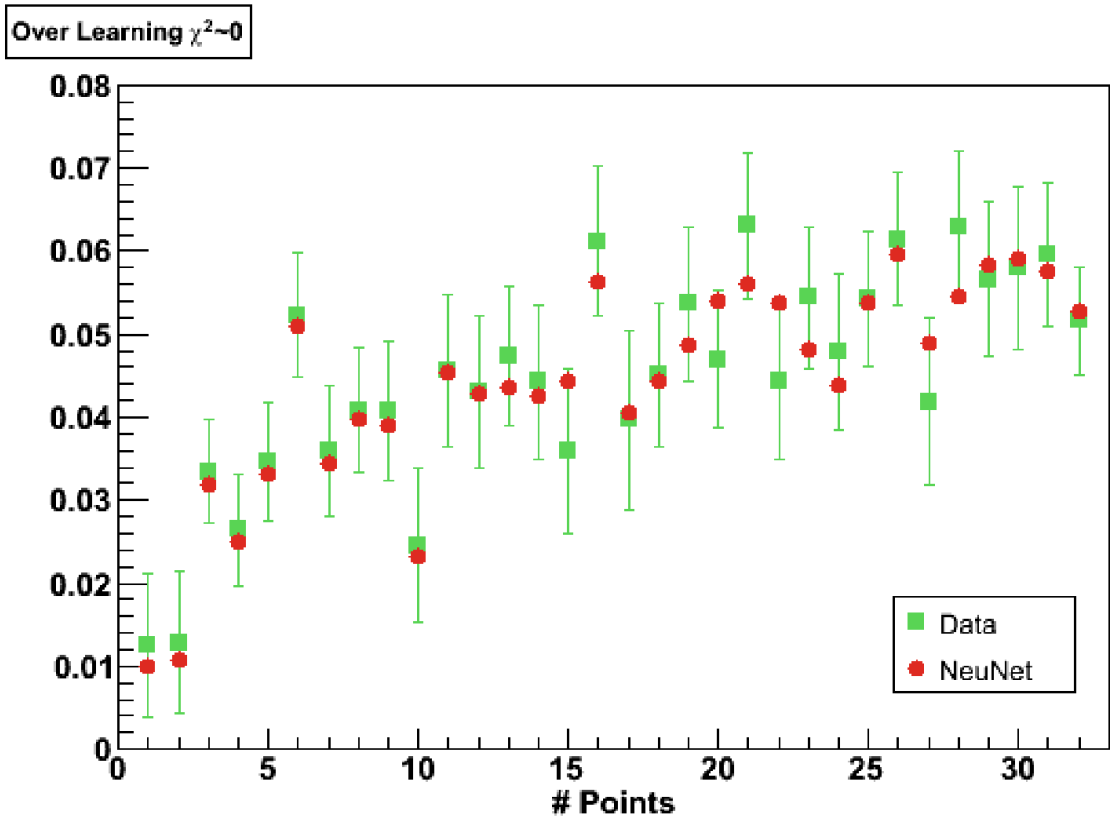
PROPER LEARNING



NEURAL LEARNING

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

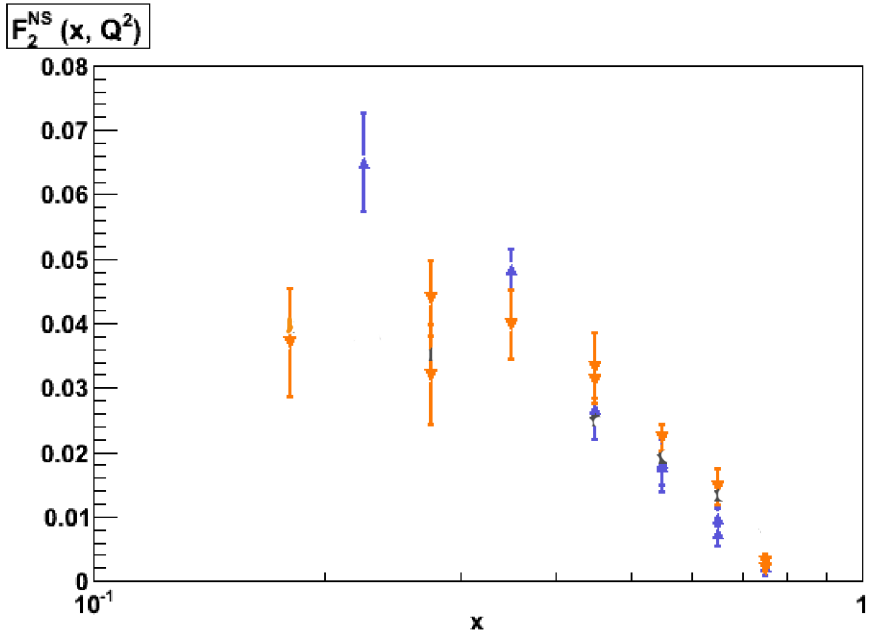
OVERLEARNING



OPTIMAL FIT: CROSS-VALIDATION

GENETIC MINIMIZATION:
AT EACH GENERATION, χ^2 EITHER UNCHANGED OR DECREASING

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



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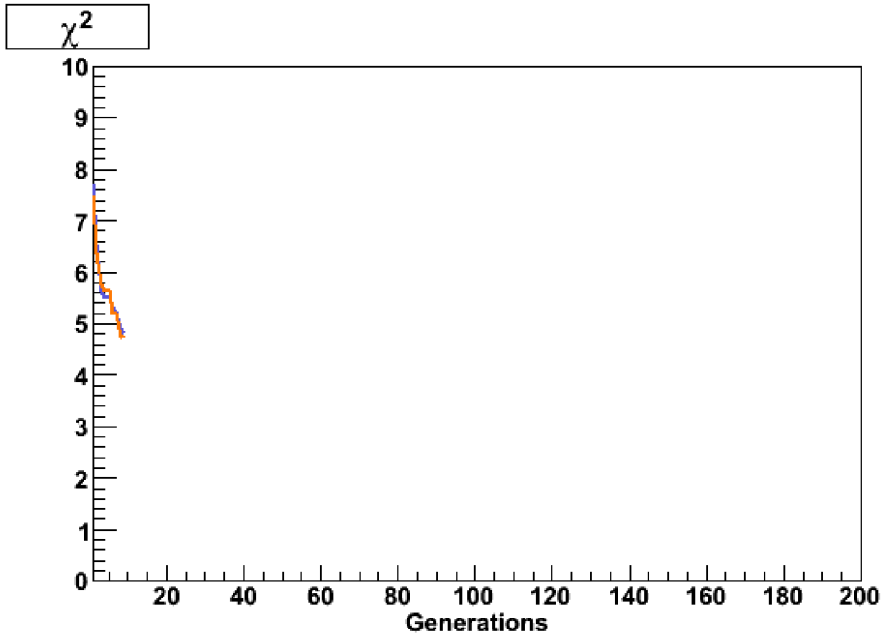
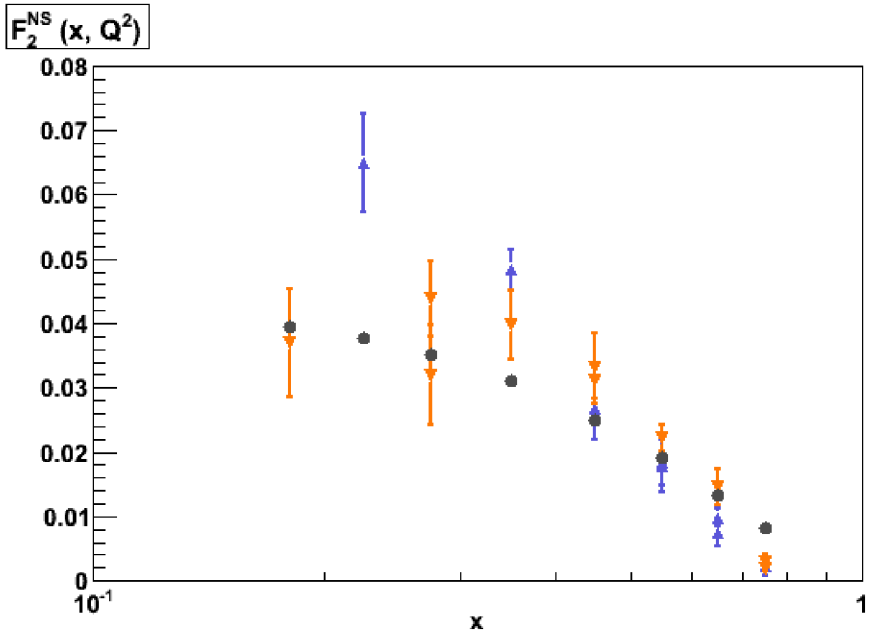
GO!





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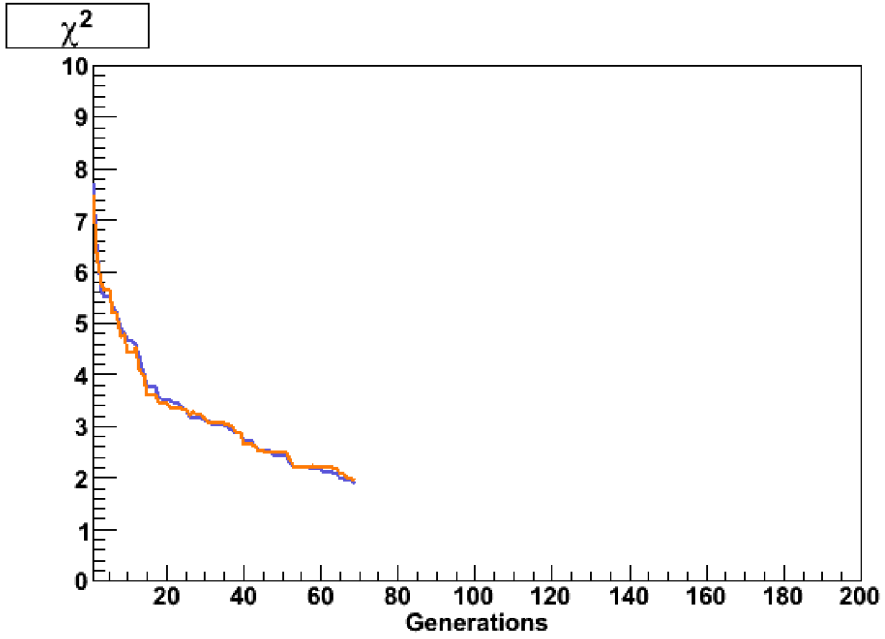
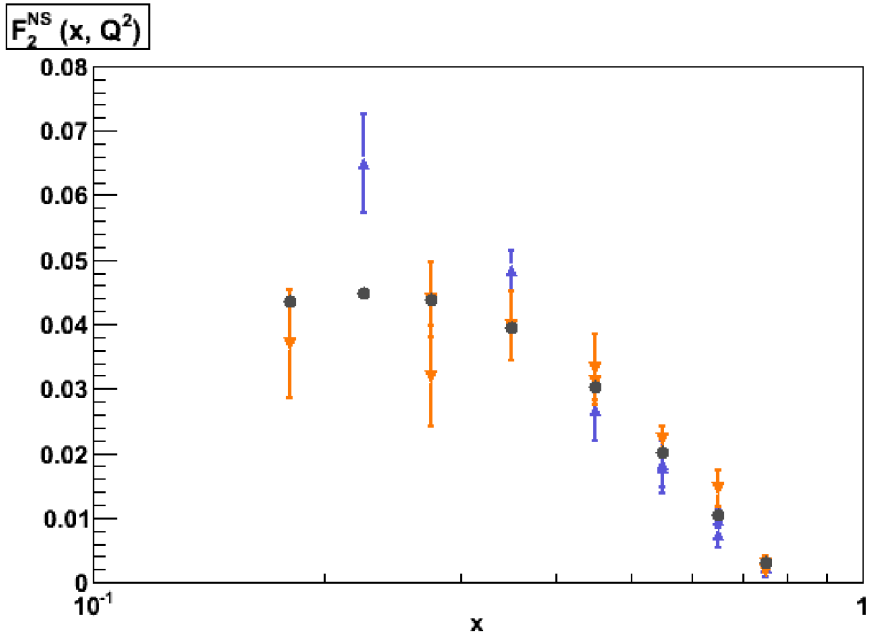
- WHEN THE VALIDATION χ^2 STOPS DECREASING, STOP THE FIT

STOP!





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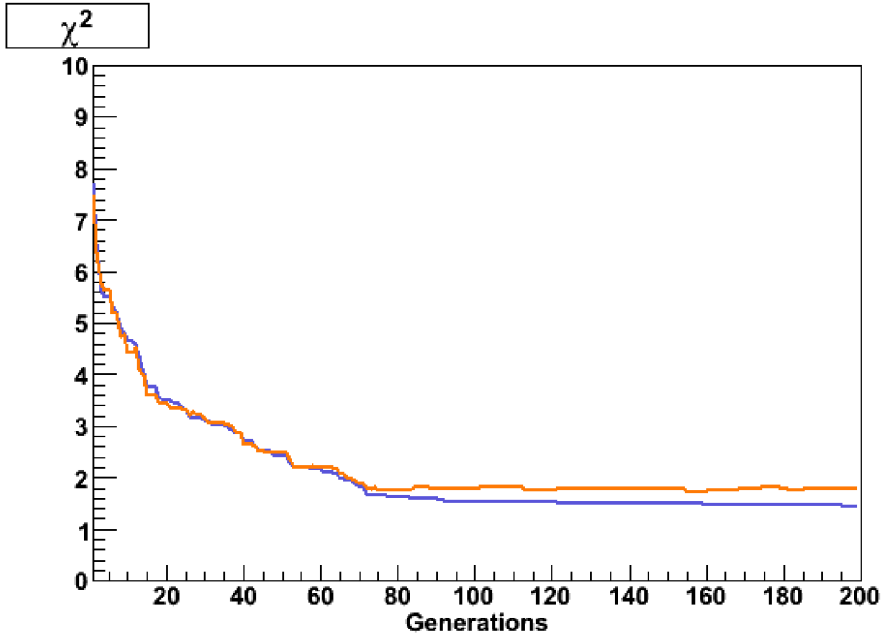
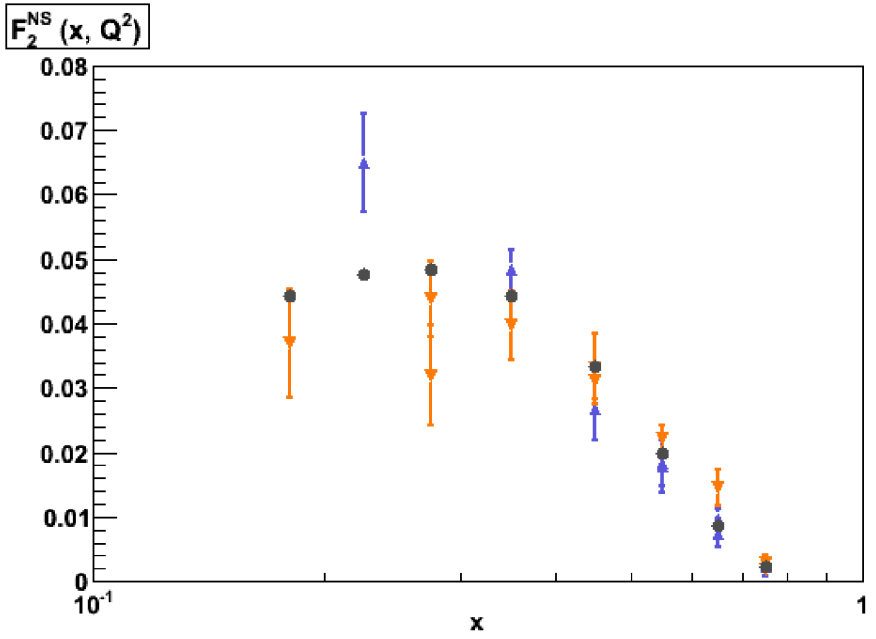
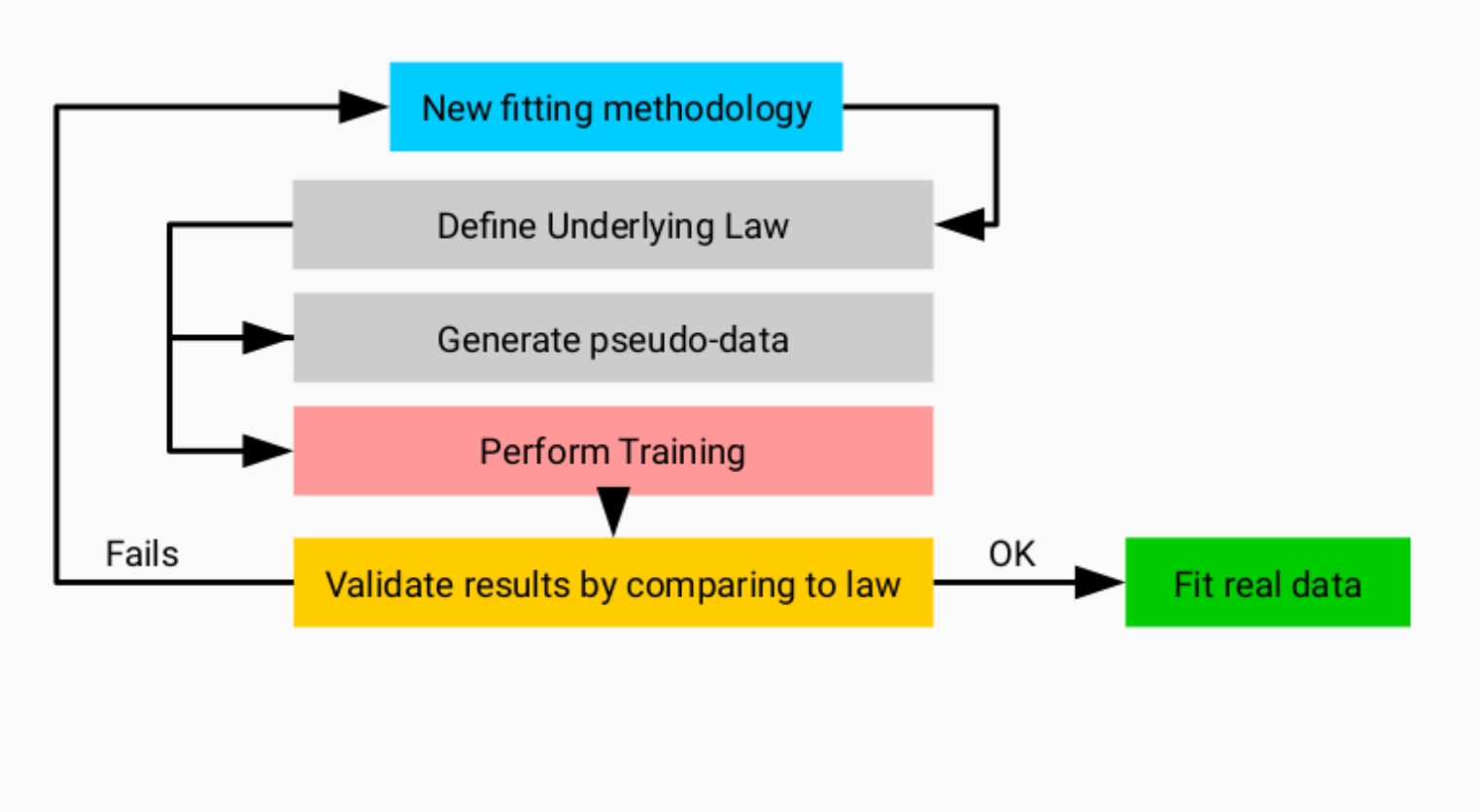
TOO LATE!





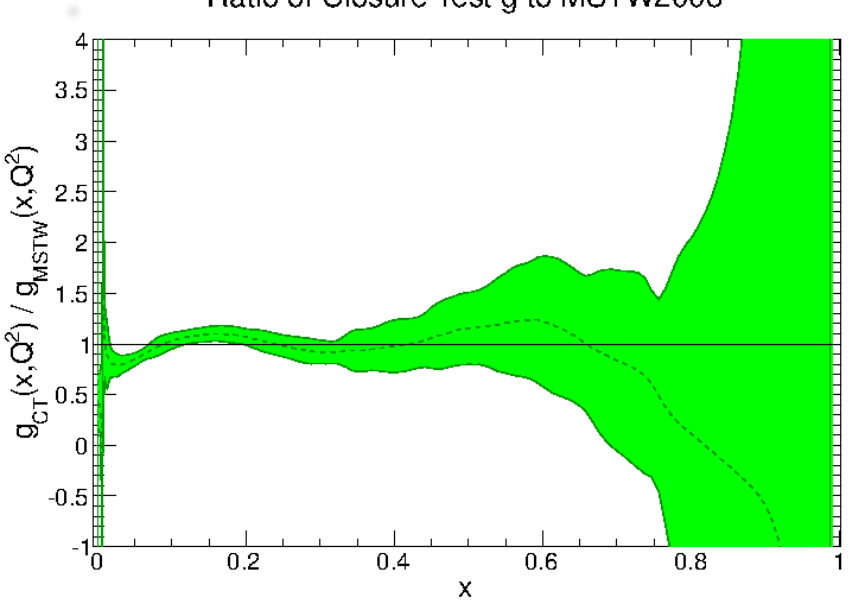
HOW DO WE KNOW THAT WE GOT THE RIGHT ANSWER?

CLOSURE TEST

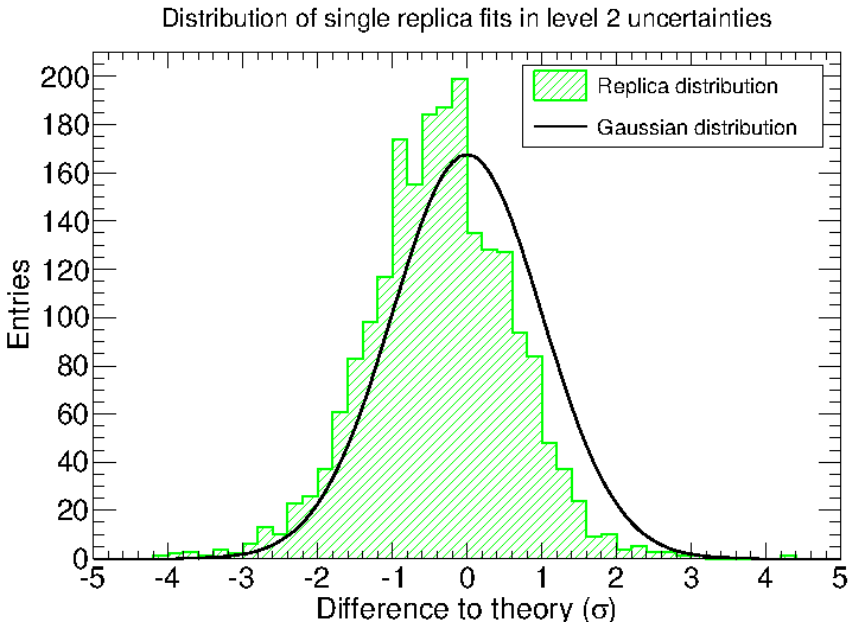


FIRST CLOSURE TEST (NNPDF3.0; 2014)

THE GLUON: RESULT/"TRUTH"



NORMALIZED DISTRIBUTION OF DEVIATIONS



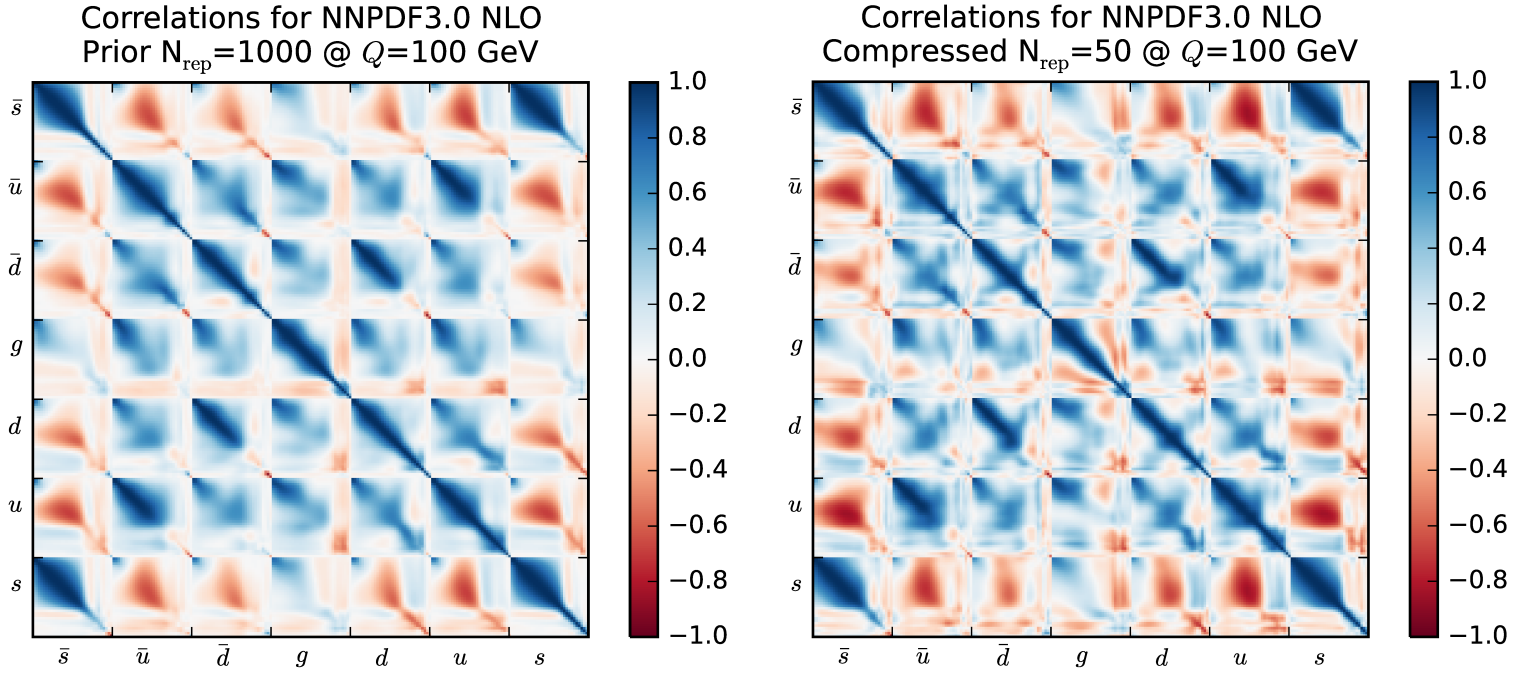
1 σ: 70% (should be 68%)

- THE METHODOLOGY IS FAITHFUL
- BUT IS IT OPTIMAL?

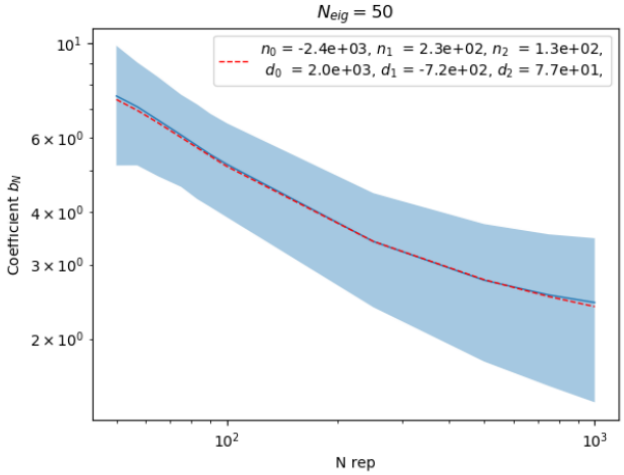
ML: UNSUPERVISED LEARNING
OPTIMIZATION I

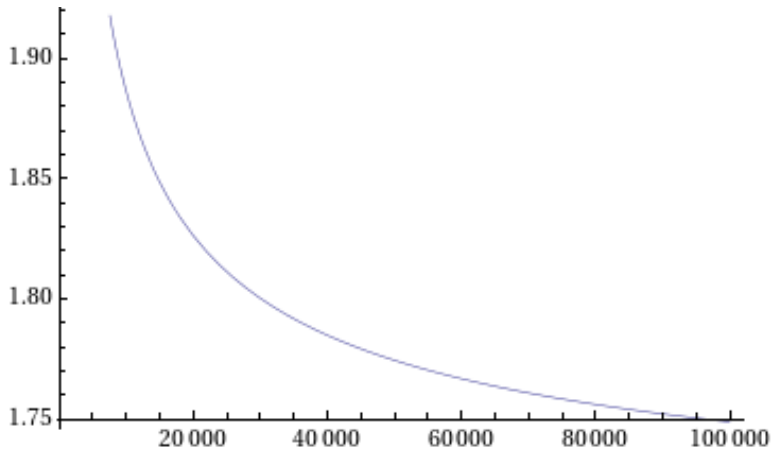
- HOW TO MAXIMIZE ACCURACY?
- LARGE (PRIOR) REPLICA SET
- GENETIC SELECTION $\Rightarrow$ OPTIMIZATION OF STATISTICAL INDICATORS (KULLBACK-LEIBLER DIVERGENCE)
- 50 OPTIMIZES REPLICAS $\Leftrightarrow$ 1000 STARTING REPLICAS

CORRELATION MATRIX



ML: SUPERVISED LEARNING
OPTIMIZATION II
HOW MANY PDF REPLICAS DO WE NEED?
FINITE-SIZE EFFECTS
ONE-σ $\Delta\chi^2$ VS NUMBER OF REPLICAS





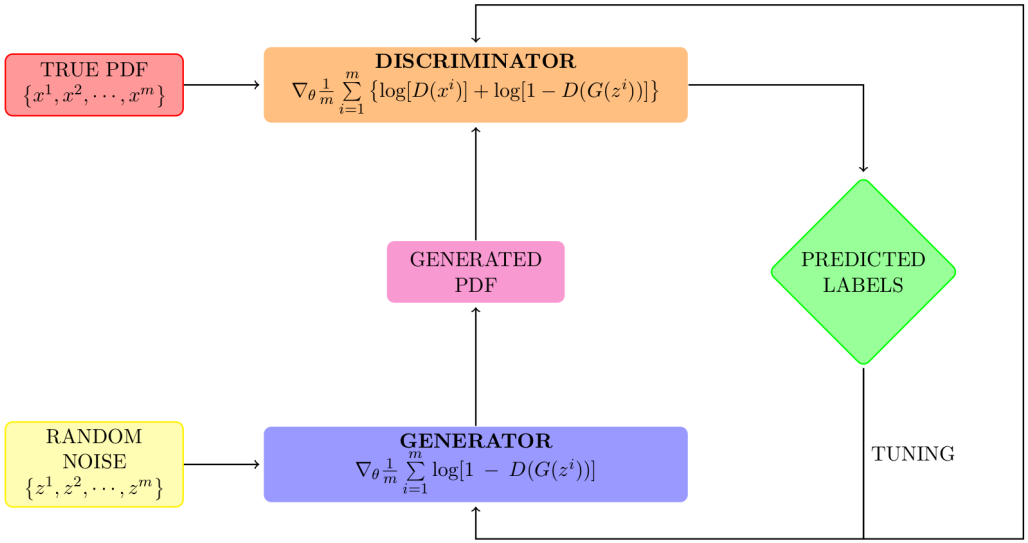
- SIGNIFICANT DEPENDENCE ON NUMBER OF REPLICAS
- ASYMPTOTIC "TOLERANCE" $T = 1.3 \pm 0.3$; $\Delta\chi^2 = 1.7 \pm 0.7$
- FOR $N_{\rm rep} = 100$, $T = 2.3$, EVEN FOR $N_{\rm rep} = 1000$, $T = 1.6$

DO WE HAVE TO FIT 10000 REPLICAS? DO WE HAVE TO USE 10000 REPLICAS?

ML: SUPERVISED LEARNING
OPTIMIZATION II

- CAN WE REDUCE THE NUMBER OF COMPRESSED REPLICAS WITHOUT LOSS OF INFORMATION? SOLUTION FOR USER
- CAN WE INCREASE THE NUMBER OF REPLICAS WITHOUT REFITTING? SOLUTION FOR PDF FITTER

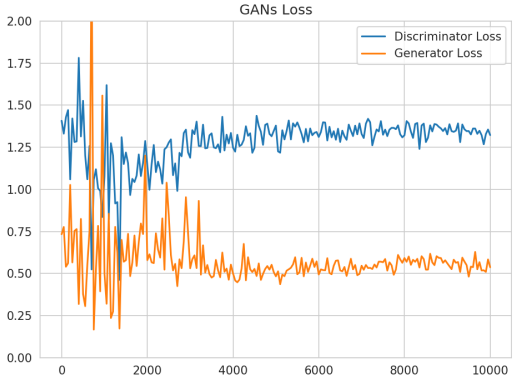
GENERATIVE ADVERSARIAL NETWORKS



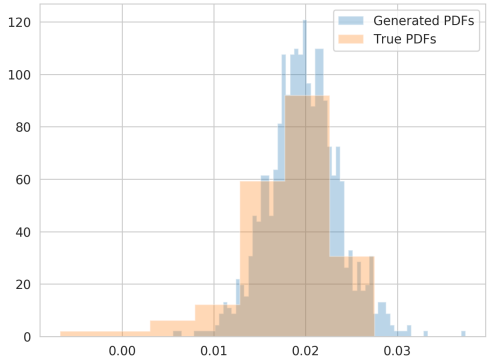
- TRAIN A NETWORK TO SIMULATE THE TRUE DISTRIBUTION (GENERATOR)
- TRAIN A NETWORK TO DISCRIMINATE TRUTH FROM SIMULATION (DISCRIMINATOR)
- TRAIN THE GENERATOR TO TRICK THE DISCRIMINATOR

SOLVING THE PROBLEM....
GAN REPLICA GENERATION

GAN TRAINING



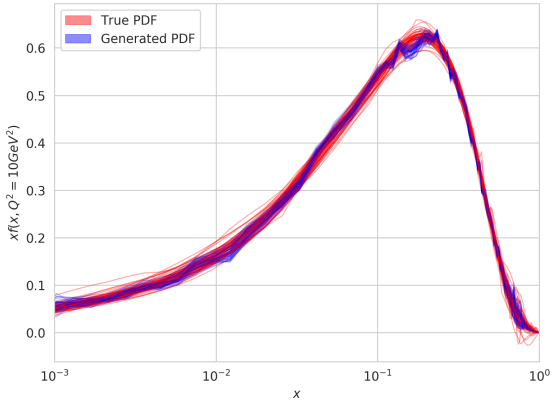
UP VALENCE AT FIXED x



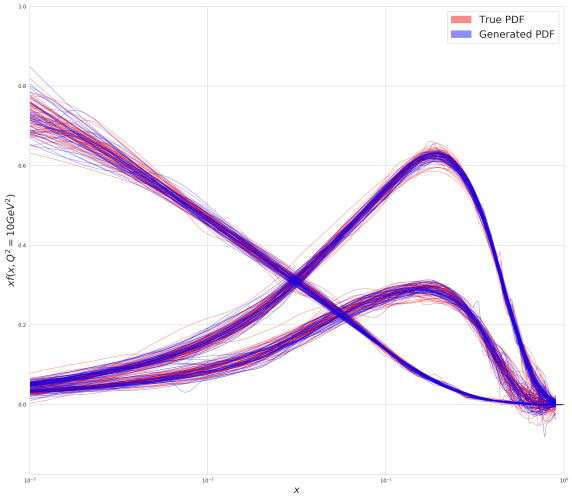
- 1D GAN: REPRODUCE THE INFORMATION IN THE UNDERLYING REPLICA SET, BUT NO GAIN (WIGGLY REPLICAS)
  $\Rightarrow$ REDUCE THE NUMBER OF COMPRESSED REPLICA WITH FIXED NUMBER OF FITTED REPLICAS W/O INFORMATION LOSS
- 2D GAN: COMBINE CORRELATED INFORMATION FROM UNDERLYING REPLICA SET INFERRING THE TRUE UNDERLYING DISTTRIBUTION
  $\Rightarrow$ REDUCE THE NUMBER OF INPUT REPLICAS W/O INFORMATION LOSS

NNPDF
Machine Learning • PDFs • QCD

ONE-DIMENSIONAL



TWO-DIMENSIONAL

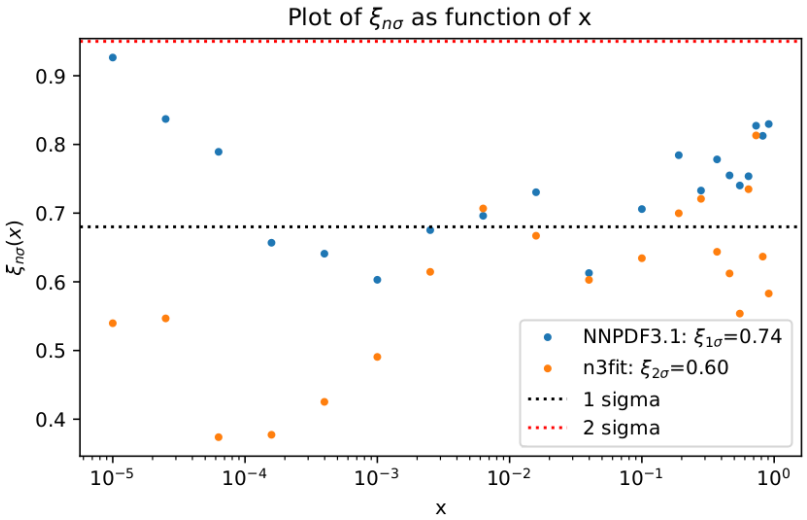


CLOSURE TEST: A CLOSER LOOK (NNPDF3.1)

ONE σ: ACTUAL/PREDICTED FOR DATA, BY EXPERIMENT

experiment	NNPDF3.1 ratio
NMC	0.882828
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

ONE σ VALUE FOR PDFS, VS x



- UNCERTAINTIES OVERESTIMATED
- 1 σ>68% AT VERY SMALL AND VERY LARGE x;
  1 σ <68% AT INTERMEDIATE x

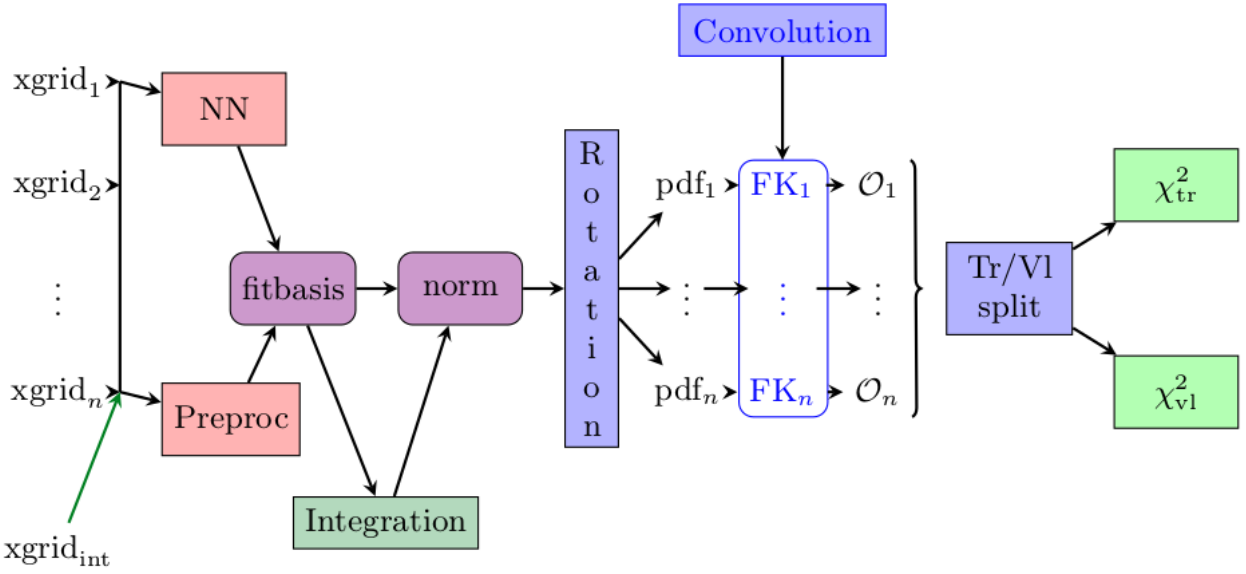
CAN WE DO BETTER?

FITTING THE METHODOLOGY

THE N3FIT PROJECT

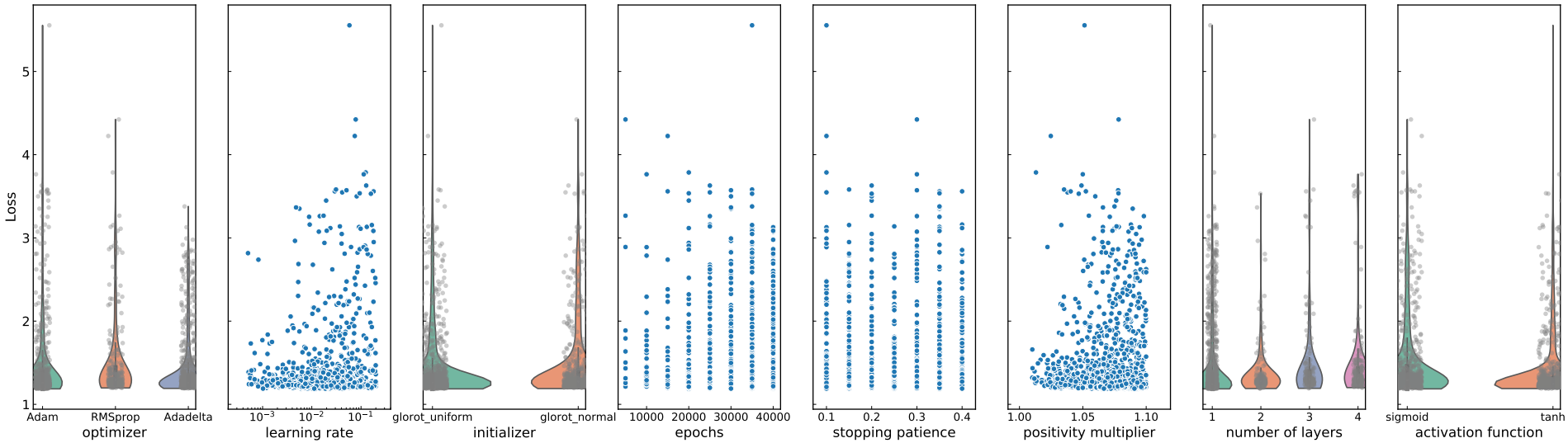
HOW DO WE KNOW THAT THE METHODOLOGY IS THE BEST?
"ACCUMULATED WISDOM" INEFFICIENT AND SLOW

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



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

FITTING THE METHODOLOGY
HYPEROPTIMIZATION SCANS



HYPEROPT PARAMETERS

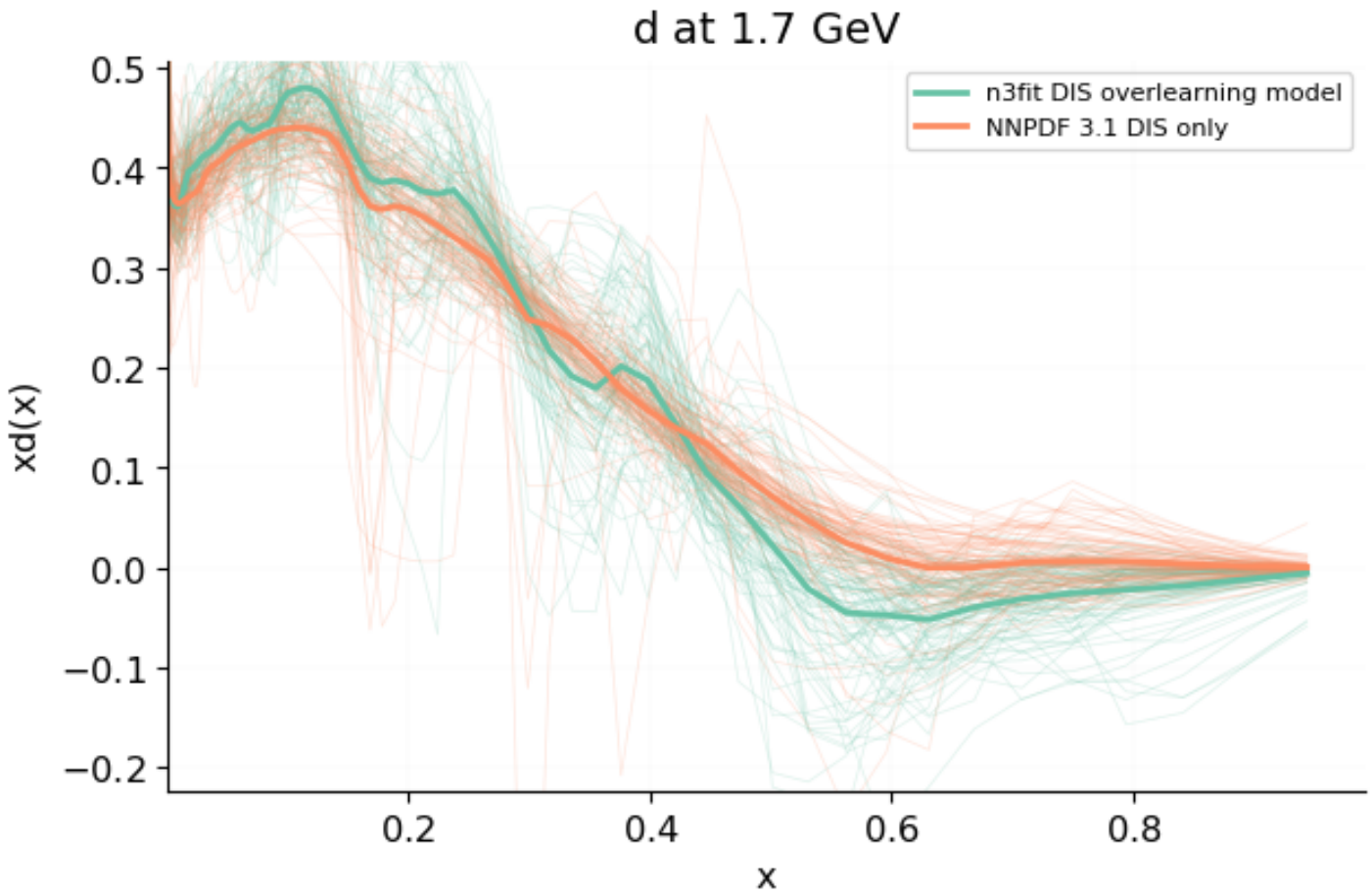
Neural Network	Fit options
Number of layers (*)	Optimizer (*)
Size of each layer	Initial learning rate (*)
Dropout	Maximum number of epochs (*)
Activation functions (*)	Stopping Patience (*)
Initialization functions (*)	Positivity multiplier (*)

- SCAN PARAMETER SPACE
- OPTIMIZE FIGURE OF MERIT: VALIDATION χ^2
- BAYESIAN UPDATING

FITTING THE METHODOLOGY

THE OVERFITTING PROBLEM

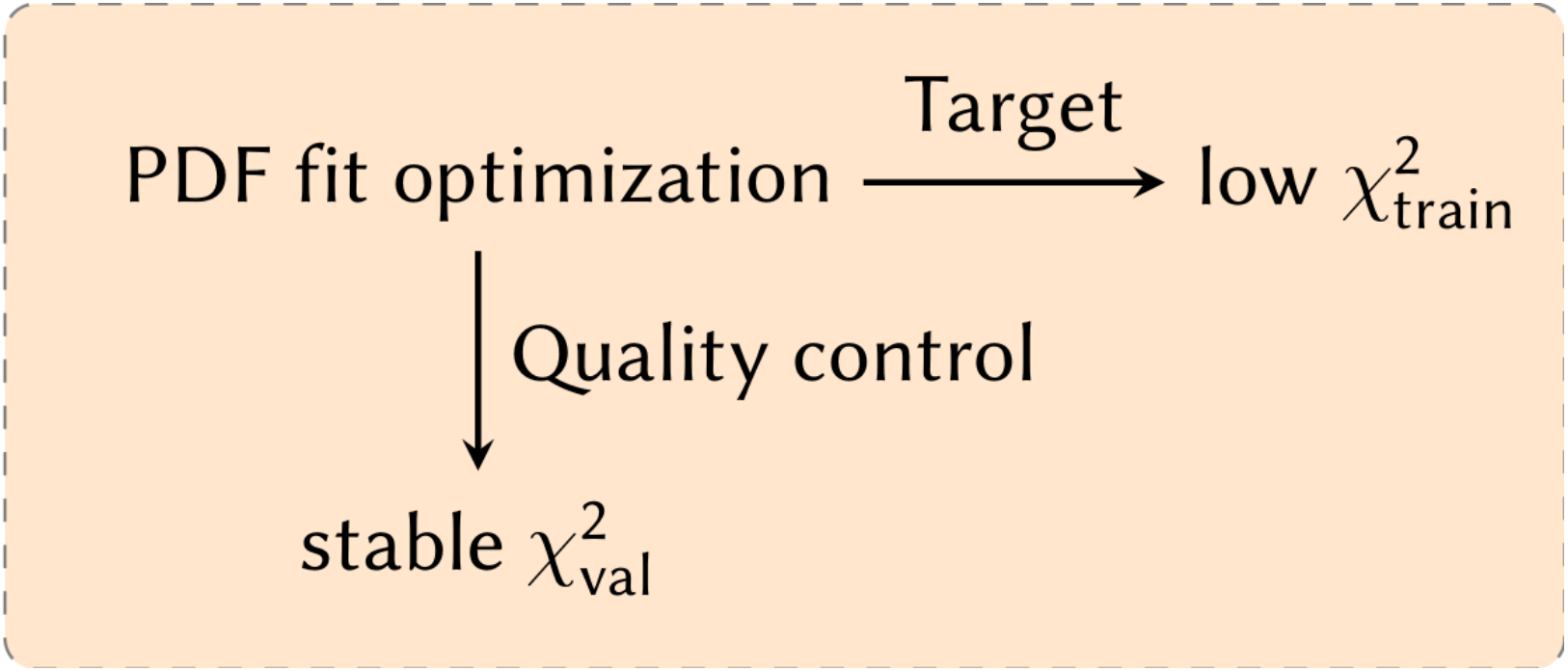
DOWN QUARK: HYPEROPTIMIZED VS. STANDARD



- OVERFITTING $\Rightarrow \chi^2_{\rm train} << \chi^2_{\rm valid}$!! & WIGGLY PDFS
- CORRELATIONS BETWEEN DATA IN A SET

WHAT HAPPENED?

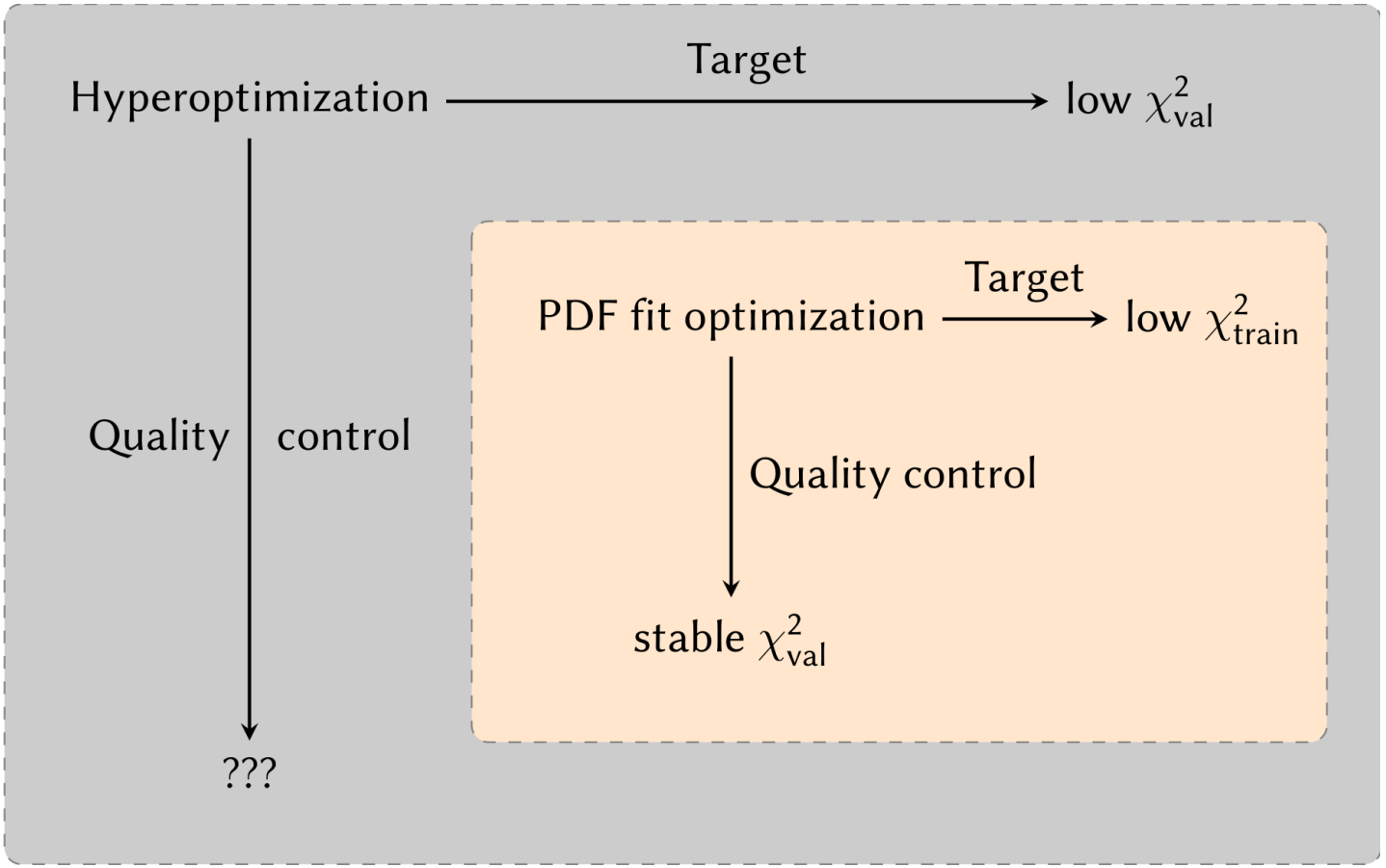
OPTIMIZATION



CROSS-VALIDATION SELECTS THE OPTIMAL MINIMUM

WHAT HAPPENED?

HYPEROPTIMIZATION

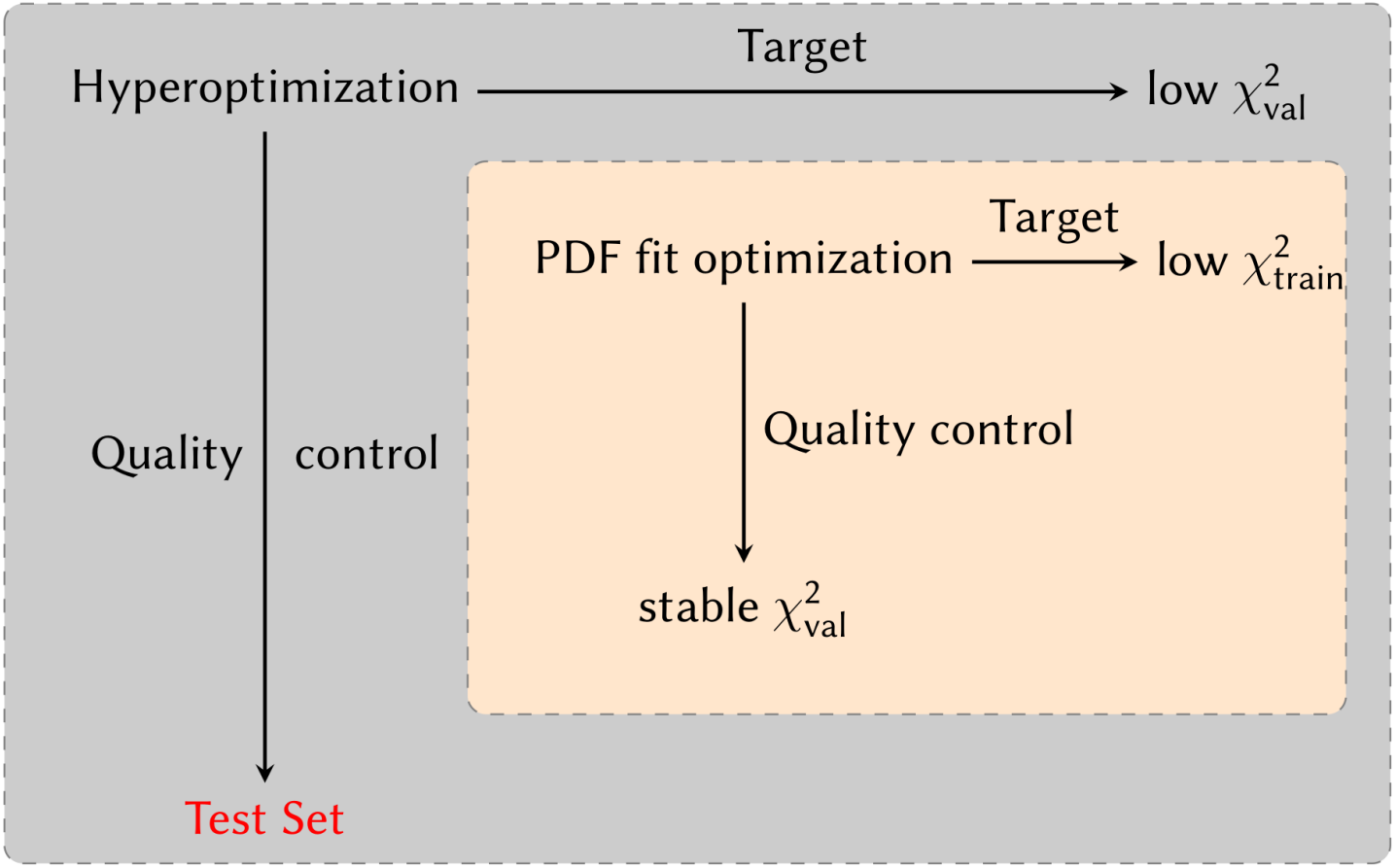


WE ARE MISSING A SELECTION CRITERION

MACHINE LEARNING

THE SOLUTION

TUNED HYPEROPTIMIZATION



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

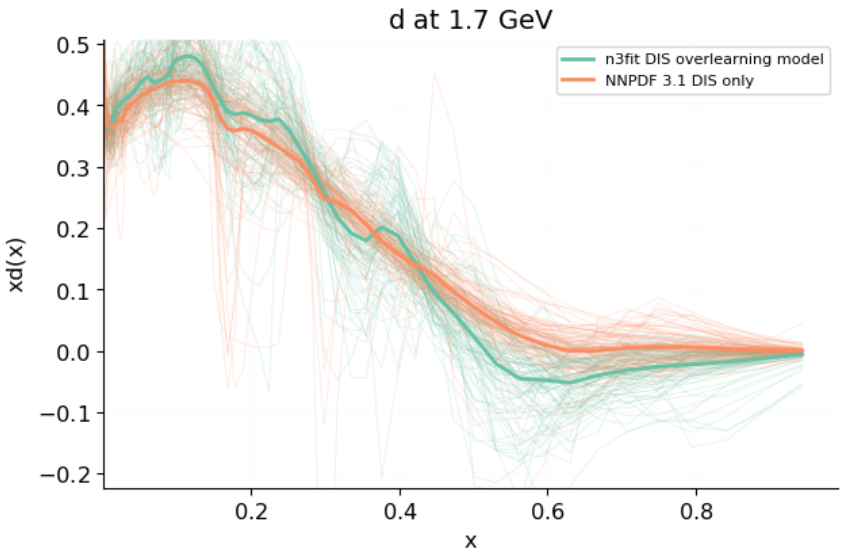
THE TEST SET METHOD

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

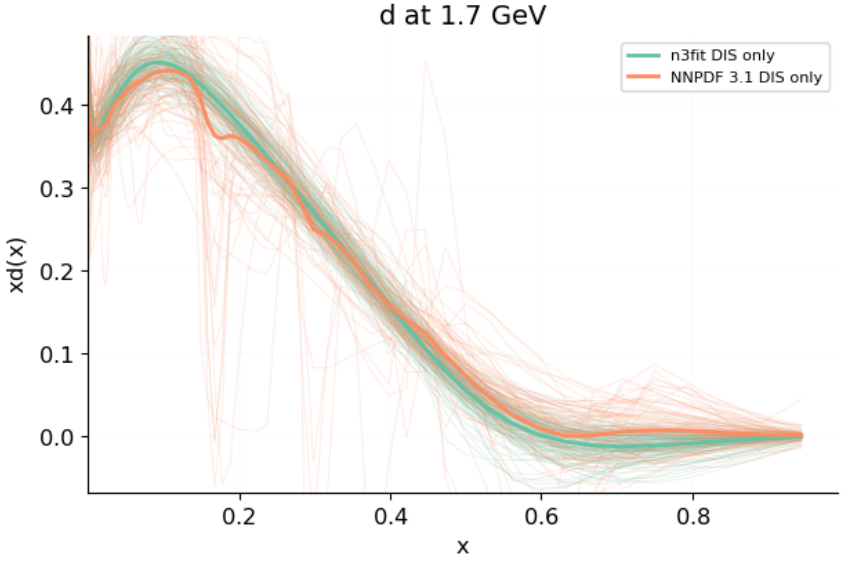
OPTIMIZED PDFS

DOWN QUARK

N3 OVERFIT VS NNPDF3.1



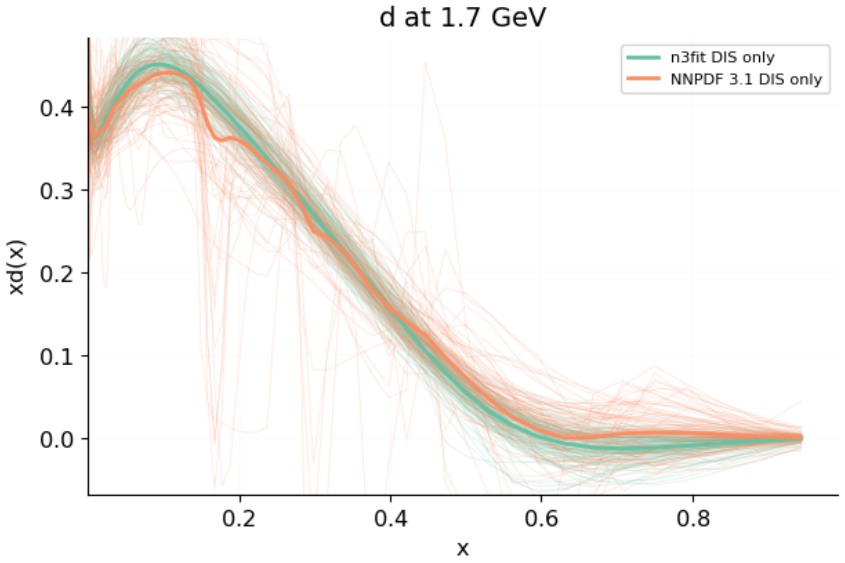
N3FIT VS NNPDF3.1



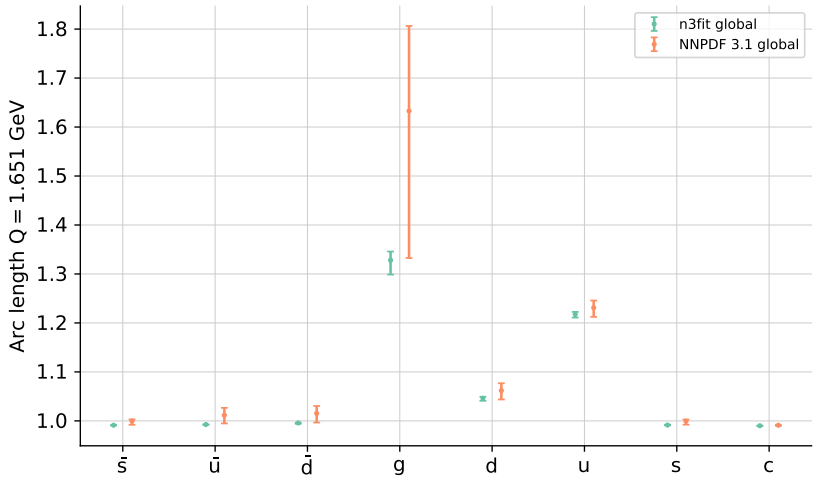
THE TEST SET METHOD

N3FIT VS NNPDF3.1

DOWN PDF



ARCLENGTHS



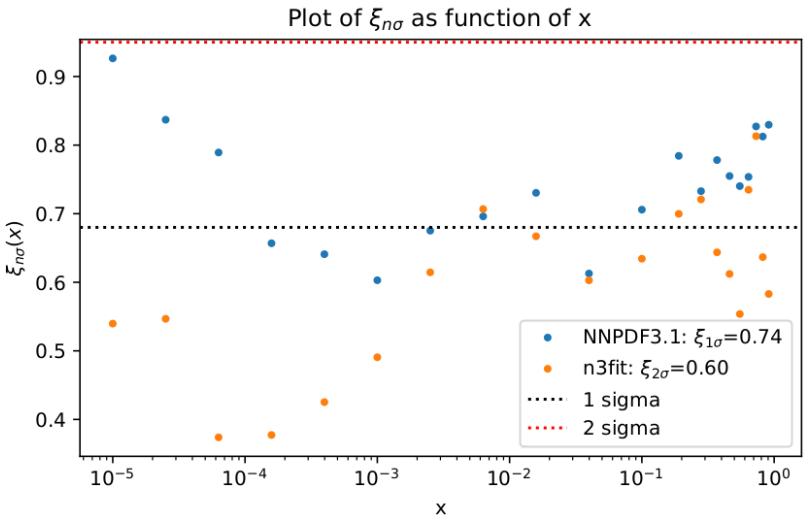
- NO OVERFITTING
- COMPARED TO NNPDF3.1
  - MUCH GREATER STABILITY $\Rightarrow$ FEWER REPLICAS FOR EQUAL ACCURACY
  - UNCERTAINTIES SOMEWHAT REDUCED

CLOSURE TESTS AGAIN

ONE σ: ACTUAL/PREDICTED FOR DATA, BY EXPERIMENT

experiment	NNPDF3.1 ratio	n3fit ratio
NMC	0.882828	0.843427
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

ONE σ VALUE FOR PDFS, VS x

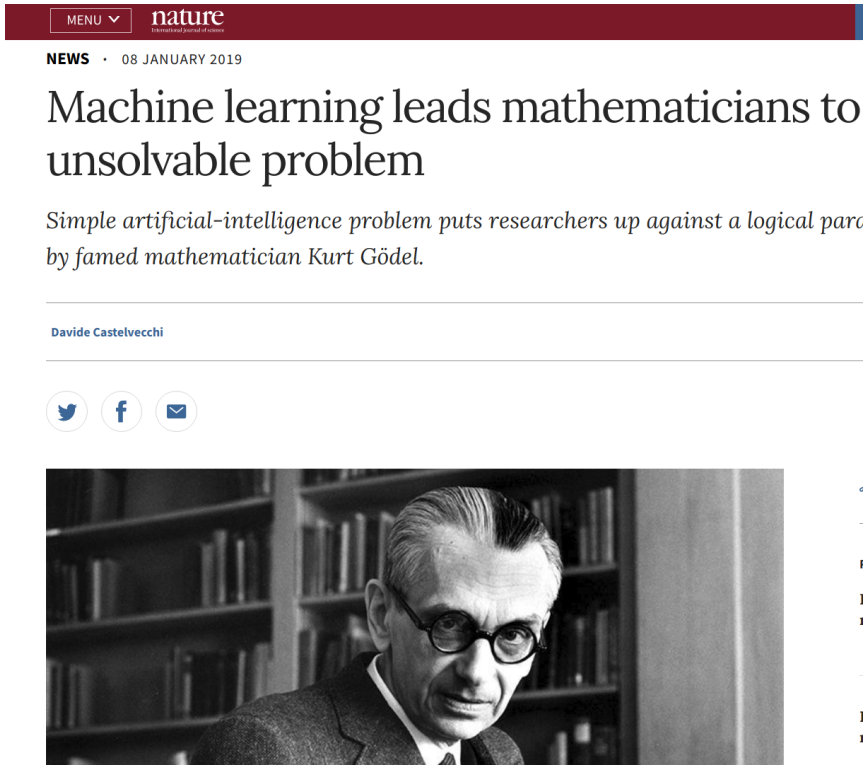


- UNCERTAINTIES WELL ESTIMATED; BUT OVERESTIMATED FOR DIS
- ONE σ PERFECT IN DATA REGION; BUT UNDERESTIMATED IN EXTRAPOLATION

WHAT ARE UNCERTAINTIES WHEN THERE ARE NO DATA?

WHAT IS "PROPER LEARNING"?

FORECASTING AN UNKNOWN TRUTH $\Rightarrow$ WHAT IS "OPTIMAL"?



MENU nature

NEWS · 08 JANUARY 2019

Machine learning leads mathematicians to unsolvable problem

Simple artificial-intelligence problem puts researchers up against a logical parc by famed mathematician Kurt Gödel.

Davide Castelvecchi

SOME POSSIBLE ANSWERS/CRITERIA

- PASS A CLOSURE TEST
- PASS A "FUTURE TEST":
  GENERALIZE TO CURRENT DATA BASED ON PAST DATA
- REPRODUCE THE EXPECTED STATISTICAL PROPERTIES:
  ONE $\sigma \Leftrightarrow \Delta\chi^2 = 1$
- SATISFY THEORETICAL PREJUDICE?

REINFORCEMENT LEARNING?

THE WORK OF MANY PEOPLE

NNPDF collaboration and N^{3}PDF team meeting,
Varenna, Italy, September 2019

“Io stimo più il trovare un vero, benché di cosa leggiera, che il disputar lungamente delle massime questioni senza verità nissuna”

“I am more interested in uncovering a fact, however trifling, than to dispute at length about profound questions devoid of any truth”

Galileo Galilei, letter to Tommaso Campanella

EXTRAS

CONTEMPORARY PDF TIMELINE (ONLY PUBLISHED GLOBAL)

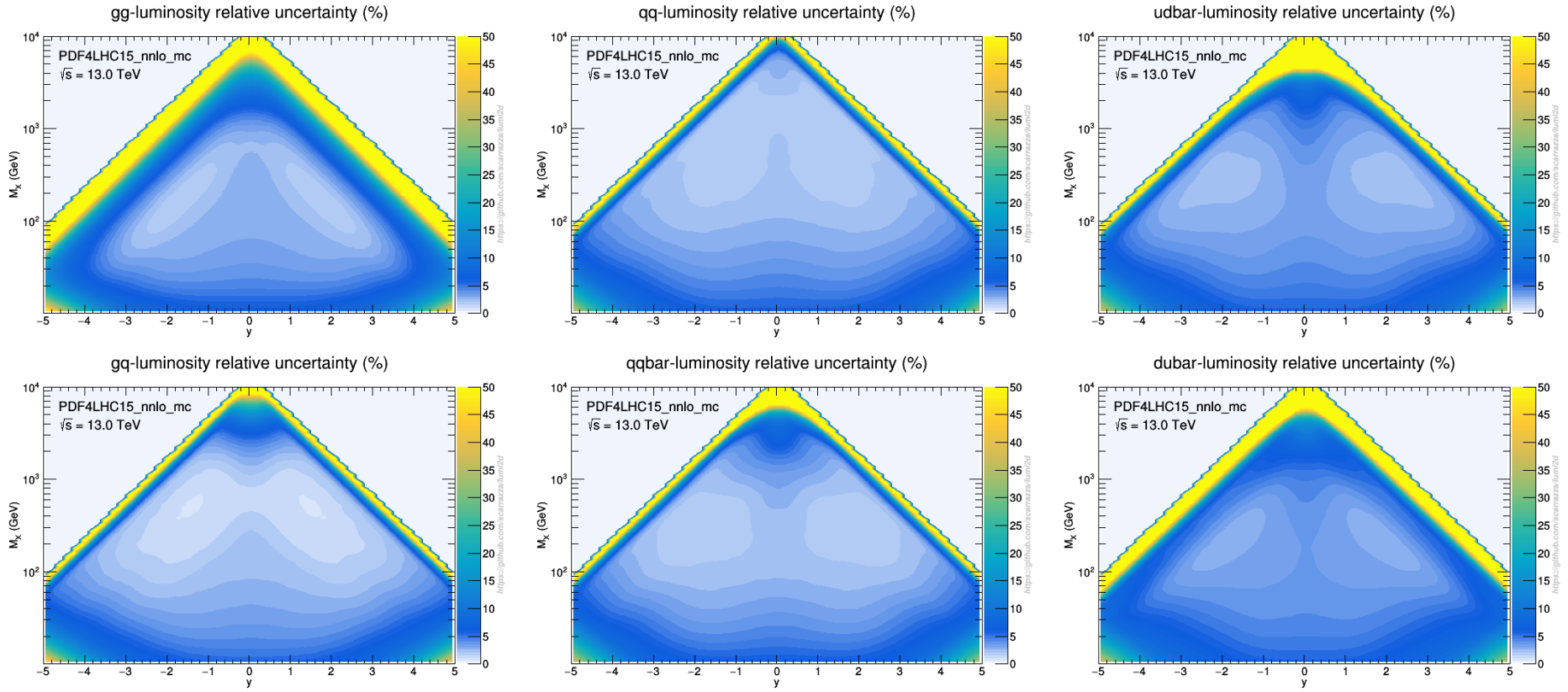
	2008		2009		2010		2011	2012		2013		2014		2015	2017		2019
SET	CTEQ6.6	NNPDF1.0	MSTW	ABKM09	NNPDF2.0	CT10 (NLO)	NNPDF2.1 (NNLO)	ABM11	NNPDF2.3	CT10 (NNLO)	ABM12	NNPDF3.0	MMHT	CT14	ABMP16	NNPDF3.1	CT18
MONTH	(02)	(08)	(01)	(08)	(02)	(07)	(07)	(02)	(07)	(02)	(10)	(10)	(12)	(06)	(01)	(06)	(12)
F. T. DIS	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
ZEUS+H1-HI	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
COMB. HI	✗	✗	✗	✗	✔	✗	✔ some	✗	✔	✗ some	✔	✔	✗	✗	✔	✔	✔
ZEUS+H1-HII	✗	✗	✗	✗	✗	✗		✗	✗		✗	✔	✗	✗	✔	✔	✔
HERA JETS	✗	✗	✔	✗	✗	✗	✗	✗	✗	✗	✗	✗	✔	✗	✗	✗	✗
F. T. DY	✔	✗	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔	✔
TEV W+Z	✔	✗	✔	✗	✔	✔	✔	✗	✔	✔	✗ some	✔	✔	✔	✗ some	✔	✔
LHC W+Z	✗	✗	✗	✗	✗	✗	✗	✗	✔	✗		✔	✔	✔		✔	✔
TEV JETS	✔	✗	✔	✗	✔	✔	✗	✔	✔	✔	✗	✔	✔	✔	✗	✔	✔
LHC JETS	✗	✗	✗	✗	✗	✗	✗	✗	✔	✗	✗	✔	✔	✔	✗	✔	✔
TOP TOTAL	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✔	✔	✗	✗	✔	✔	✔
SINGLE TOP TOTAL	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✔	✗	✗
TOP DIFFERENTIAL	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✔	✔
W p_T	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✔	✗	✗	✗	✗	✗
W+C	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✔	✗	✗	✗	✗	✗
Z p_T	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✔	✔

THEORY PROGRESS:

- MSTW, ABKM: all NNLO; NNPDF NNLO since 07/11 (2.1), CT since 02/13 (CT10);
  NNPDF THRESHOLD RESUMMATION (3.0RESUM, 07/15), SMALL x RESUMMATION (3.1SX, 10/17)
- MSTW, CT, NNPDF all GM-VFN; NNPDF since 01/11 (2.1);
  ABM FFN+ZM-VFN since 01/17 (ABMP16)
- NNPDF FITTED CHARM since 05/16 (NNPDF3IC)
- PHOTON PDF: (mrst2004qed), NNPDF2.3QED (08/13), NNPDF3.0QED (06/16), NNPDF3.1LUXQED (12/17)

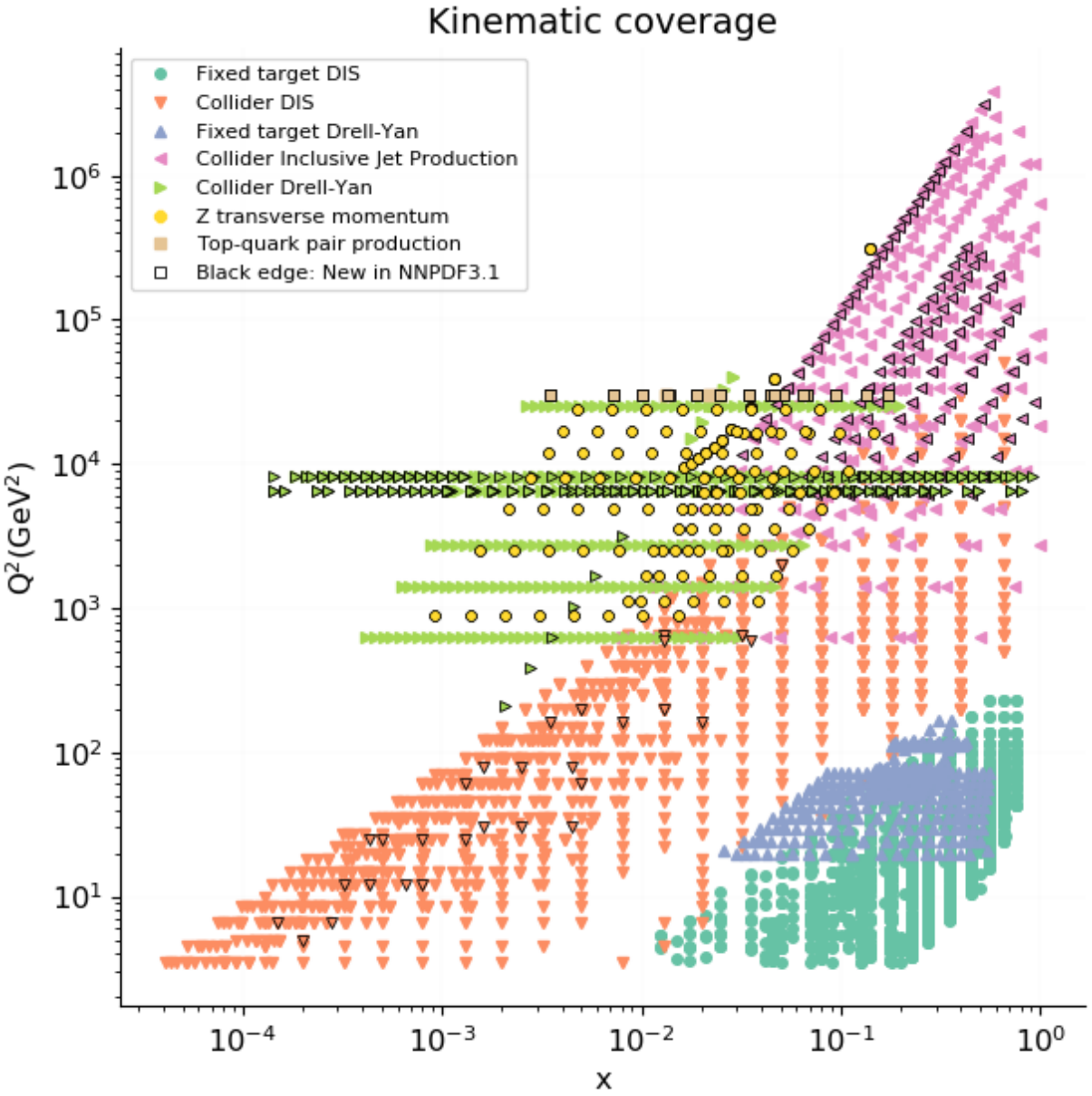
PDF4LHC15: PDF UNCERTAINTIES (NNLO)

GLUON SINGLET FLAVORS



- GLUON BETTER KNOWN AT SMALL x, VALENCE QUARKS AT LARGE x, SEA QUARKS IN BETWEEN
- TYPICAL UNCERTAINTIES IN DATA REGION $\sim 3-5\%$
- SWEET SPOT: VALENCE Q - G; DOWN TO 1%
- UP BETTER KNOWN THAN DOWN; FLAVOR SINGLET BETTER THAN INDIVIDUAL FLAVORS
- NO QUALITATIVE DIFFERENCE BETWEEN NLO AND NNLO

DATASET WIDENING
NNPDF3.0 vs NNPDF3.1



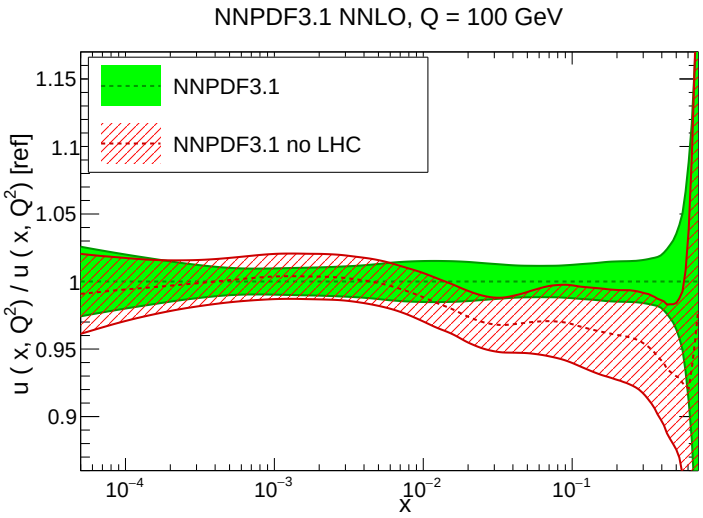
NEW DATA: (BLACK EDGE)

- HERA COMBINED F_2^b
- D0 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

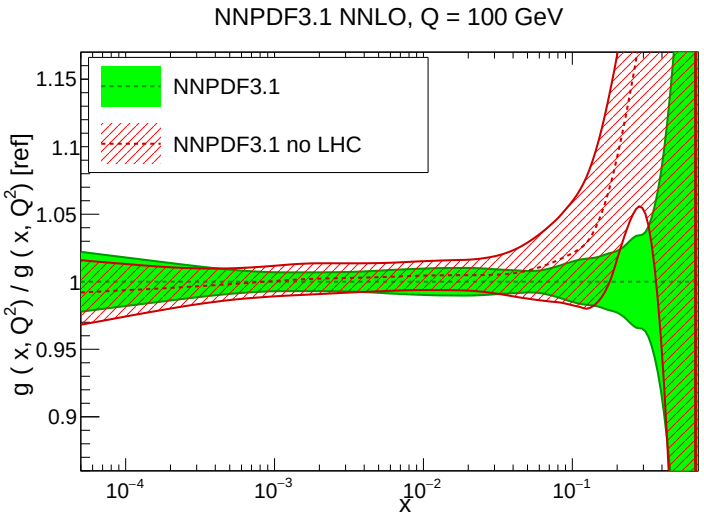
THE IMPACT OF LHC DATA

NEXT-GENERATION PDFs LARGELY DETERMINED BY LHC DATA: A FIRST!

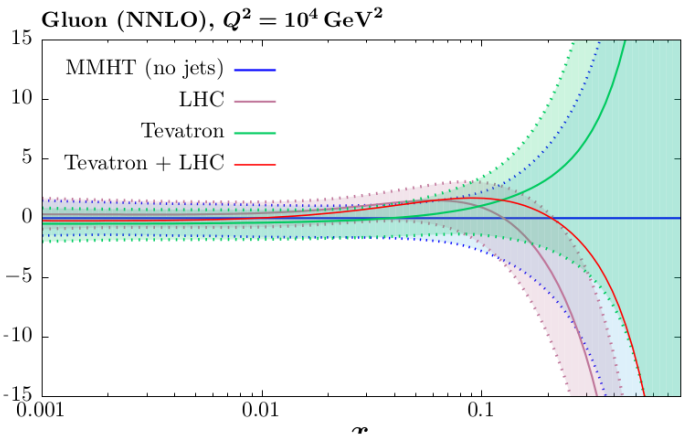
NNPDF3.1 up



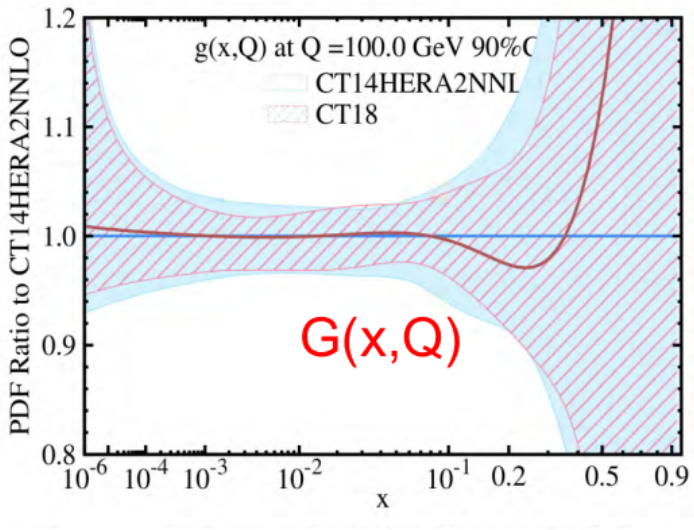
NNPDF3.1 glue



'MMHT' 19 glue (prelim., unpublished)



CT18 glue (preliminary, unpublished)



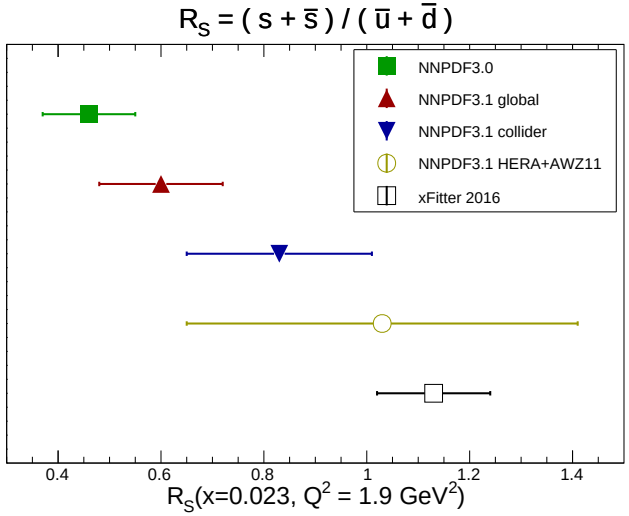
- SIGNIFICANT UNCERTAINTY REDUCTION
- MANY PDFs CHANGE BY MORE THAN ONE SIGMA
- BOTH FLAVOR SEPARATION & GLUON SIGNIFICANTLY AFFECTED

DATA VS. THEORY/METHODOLOGY
THE STRANGE PDF: DIS VS. W PRODUCTION

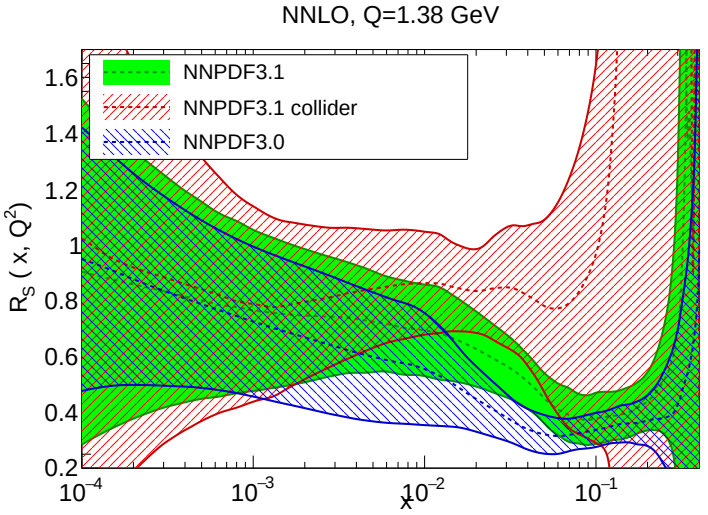
- STRANGE PDF CONTROLLED BY NEUTRINO DIS CHARM PRODUCTION + W PRODUCTION
- DIS DATA FAVOR "SUPPRESSED STRANGE" $\Rightarrow$ SMALL $R_s \equiv \frac{s+\bar{s}}{\bar{u}+\bar{d}}$
- ATLAS FAVORS ENHANCED STRANGENESS
- ATLAS IMPACT EXAGGERATED IN XFITTER ANALYSIS
- EVERYTHING CONSISTENT WITHIN UNCERTAINTIES IN GLOBAL FIT

THE STRANGENESS SUPPRESSION

XFITTER VS HERA+ATLAS VS. DIS ONLY VS ATLAS ONLY VS ALL



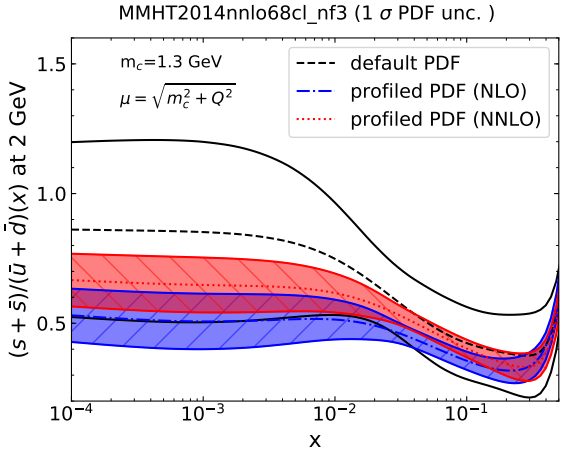
DIS ONLY VS ATLAS ONLY VS ALL



DATA VS. THEORY/METHODOLOGY
THE STRANGE PDF: DIS VS. W PRODUCTION

- MASSIVE CORRECTIONS TO CHARGED CURRENT DIS HITERTO INCLUDED TO NLO MASSLESS TO NNLO
- Gao, 2018 $\Rightarrow$ NNLO COMPUTED
- STRANGENESS ENHANCED BY NNLO CORRECTIONS

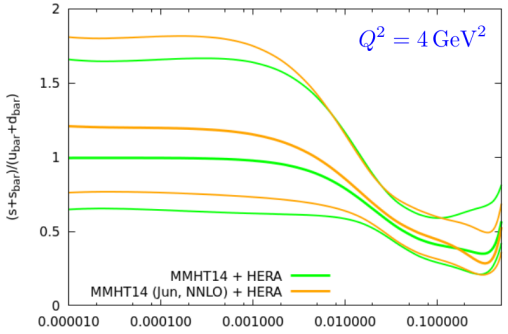
HERAPDF +NLO CC DIS VS NNLO CC DIS

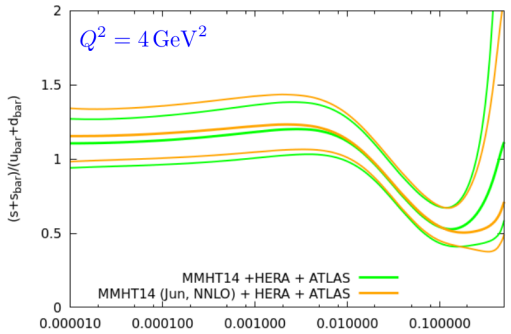


(Gao, 2108)

MMHT WITH NLO VS NNLO CC DIS

Preliminary





(Harland-Lang, Thorne, prelim.)

LESSONS:

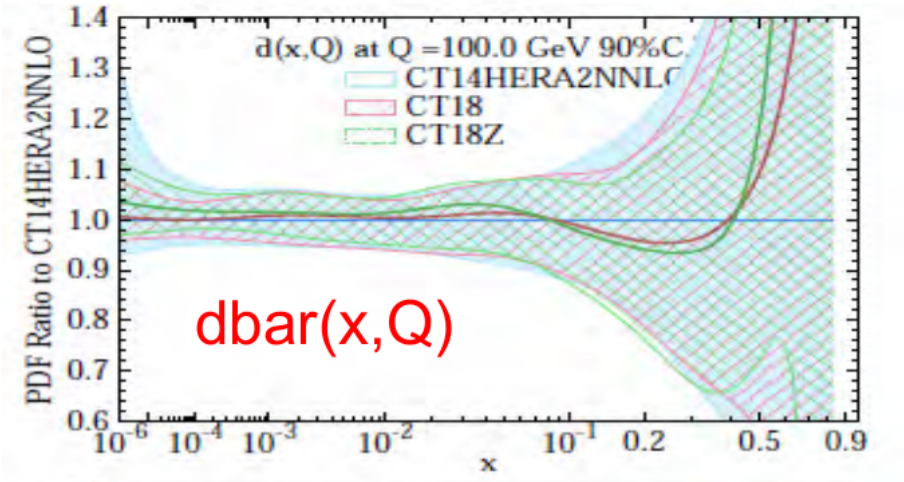
- BEWARE OF XFITTER HERA+X FITS
- IN A GLOBAL FIT DIFFERENT DATA ALWAYS PULL IN DIFFERENT DIRECTIONS!
- TENSIONS CAN BE RESOLVED BY BETTER THEORY

DATA VS. THEORY/METHODOLOGY
THE CHARM MASS AND TREATMENT
CT18 → CT18Z

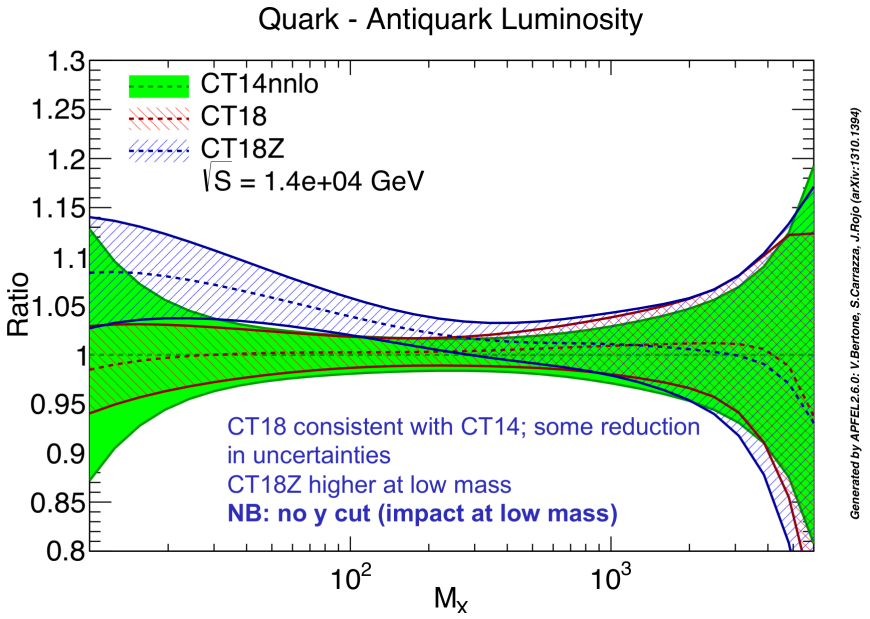
- ATLAS W AND Z 7TEV RAPIDITY INCLUDED
- CHARM MASS INCREASED
- x-DEPENDENT FACTORIZATION SCALE

CT18 VS. CT18Z (preliminary, unpublished)

DBAR PDF



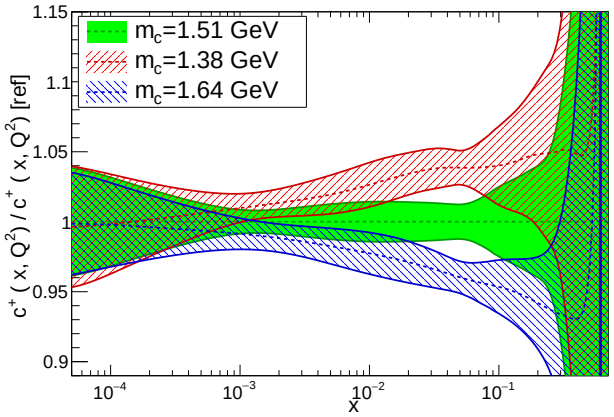
QQBAR LUMI



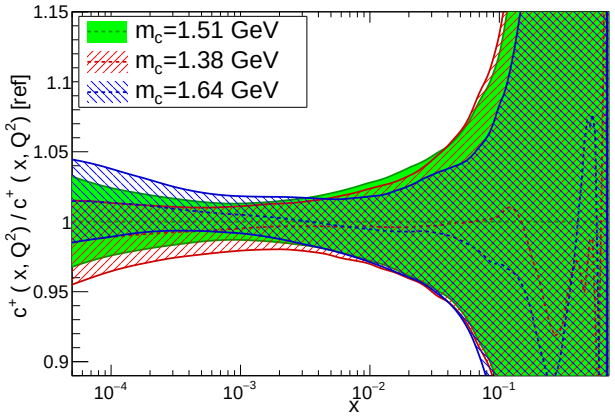
DATA VS. THEORY/METHODOLOGY
THE CHARM MASS AND TREATMENT
CHARM FROM DATA

- CHARM SHOULD NOT DEPEND STRONGLY ON CHARM MASS

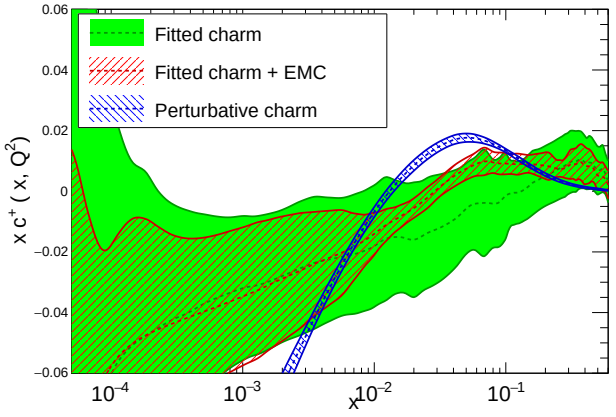
PERTURBATIVE CHARM VS m_c



FITTED CHARM VS m_c



FITTED VS. PERTURBATIVE CHARM



- ITS SHAPE SHOULD NOT BE DETERMINED BY FIRST-ORDER MATCHING (NO HIGHER NONTRIVIAL ORDERS KNOWN)
- MIGHT EVEN HAVE A NONPERTURBATIVE COMPONENT

FITTED VS. PERTURBATIVE:
SUPPRESSED AT MEDIUM-SMALL x,
ENHANCED AT VERY SMALL, VERY LARGE x

DATA VS. THEORY/METHODOLOGY

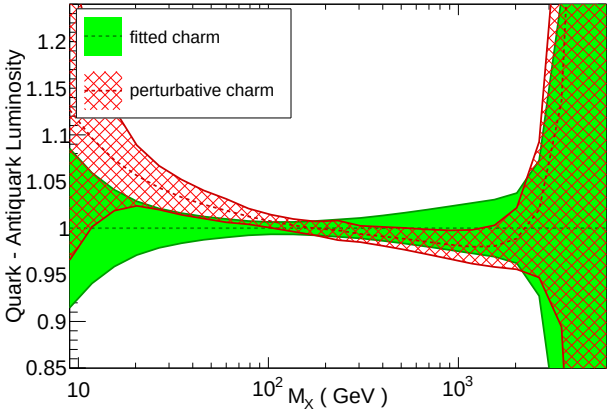
THE CHARM MASS AND TREATMENT

CHARM FROM DATA IMPACT ON LIGHT QUARK PDFS

FITTED VS. PERTURBATIVE CHARM

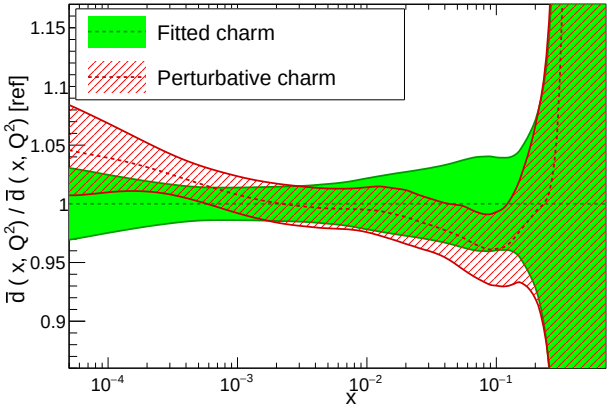
QQBAR LUMI

LHC 13 TeV, NNLO



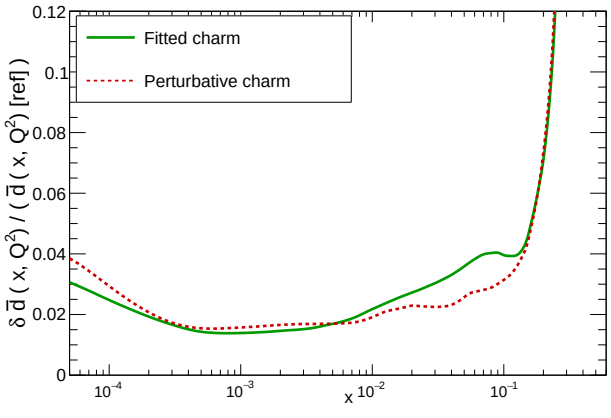
ANTIDOWN PDF

NNPDF3.1 NNLO, Q = 100 GeV



ANTIDOWN PDF UNCERTAINTY

NNPDF3.1 NNLO, Q = 100 GeV



- QUARK LUMI AFFECTED BECAUSE OF CHARM SUPPRESSION AT MEDIUM-x
- FLAVOR DECOMPOSITION ALTERED
- UNCERTAINTIES ON LIGHT QUARKS NOT SIGNIFICANTLY INCREASED
- AGREEMENT OF 13TeV W,Z PREDICTED CROSS-SECTIONS IMPROVES!

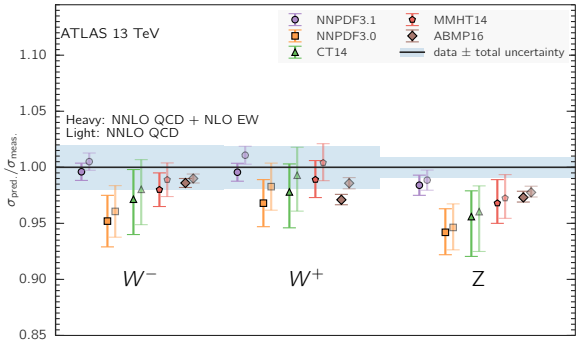
DATA VS. THEORY/METHODOLOGY

THE CHARM MASS AND TREATMENT

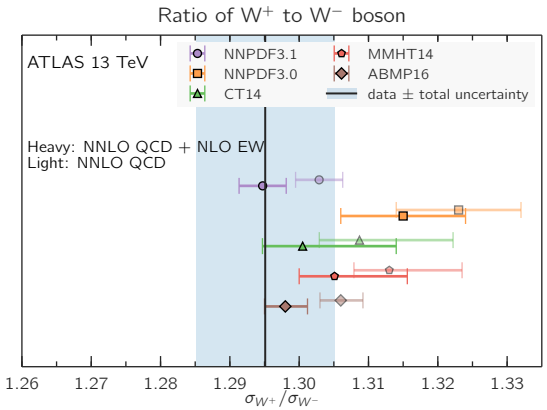
CHARM FROM DATA

IMPACT ON PHENOMENOLOGY

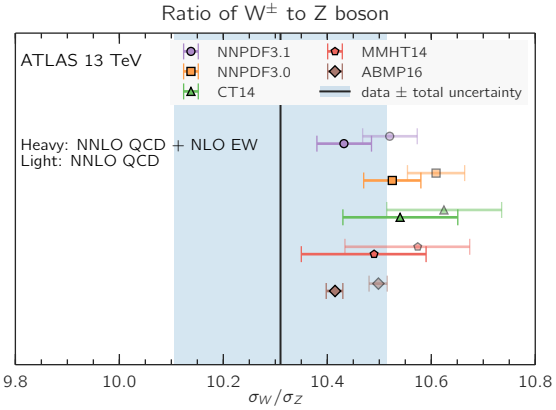
DRELL-YAN XSECTS



W^+/W^- XSECT RATIO



W/Z XSECT RATIO



- W, Z CROSS-SECTIONS AT 13 TEV IN PERFECT AGREEMENT WITH DATA
  THANKS TO FITTED CHARM!

LESSONS:

- TENSIONS CAN REVEAL METHODOLOGICAL ISSUES
- MORE LIKELY AS DATASET INCREASES, EXPERIMENTAL UNCERTAINTIES DECREASE
- RESOLVED BY MORE COMPLEX METHODOLOGY

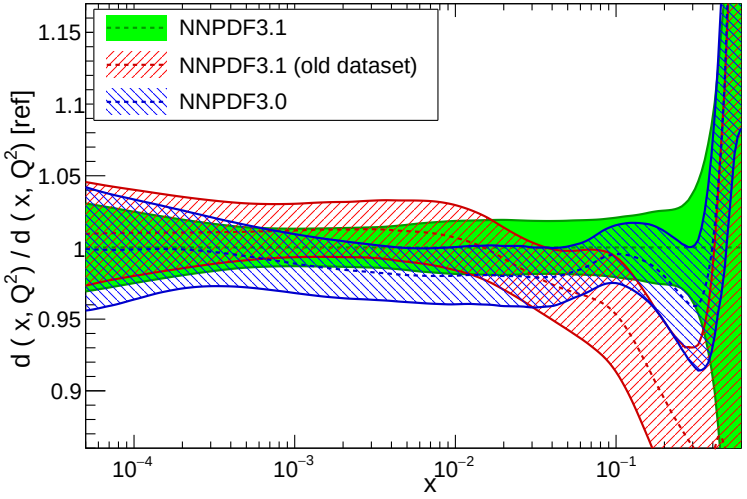
DATA vs. METHODOLOGY

- NEW DATA $\Rightarrow$ MAJOR METHODOLOGICAL CHOICES $\Rightarrow$ SIGNIFICANT IMPACT
- NNPDF3.1 vs NNPDF3.0: DATA AND METHODOLOGY HAVE SIMILAR IMPACT

NNPDF3.0 vs. NNPDF3.1 vs. NNPDF3.1 w/ NNPDF3.0 DATASET

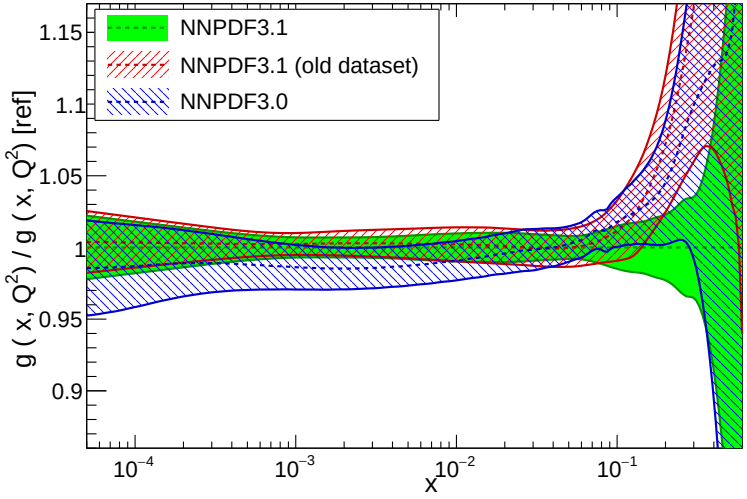
DOWN

NNLO, Q = 100 GeV



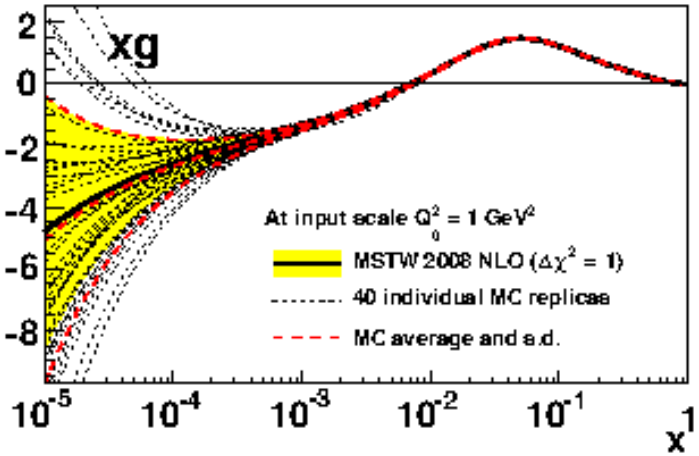
GLUON

NNLO, Q = 100 GeV

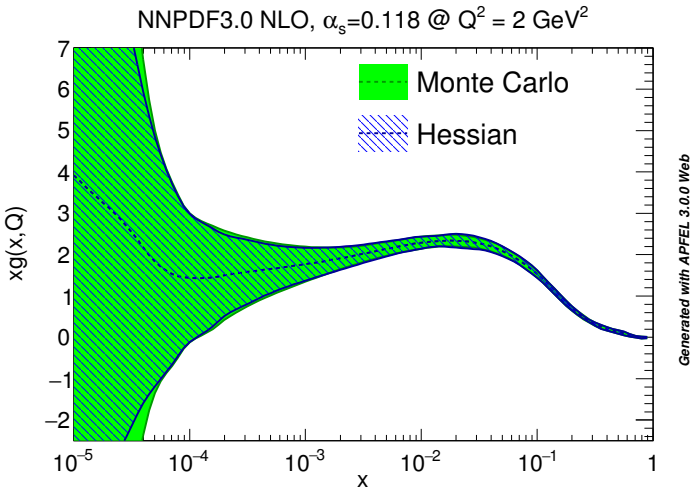


TOOLS I
MC $\Leftrightarrow$ HESSIAN

- TO CONVERT HESSIAN INTO MONTECARLO GENERATE MULTIGAUSSIAN REPLICAS IN PARAMETER SPACE
- ACCURATE WHEN NUMBER OF REPLICAS SIMILAR TO THAT WHICH REPRODUCES DATA



(Thorne, Watt, 2012)



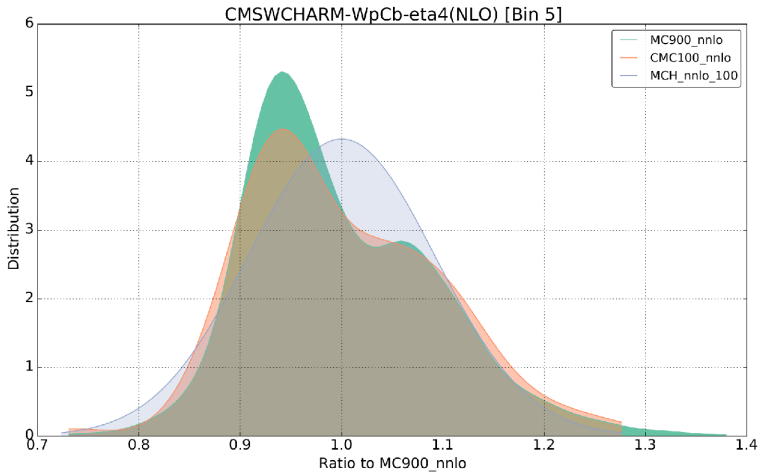
(Carrazza, SF, Kassabov, Rojo, 2015)

- TO CONVERT MONTE CARLO INTO HESSIAN, SAMPLE THE REPLICAS $f_i(x)$ AT A DISCRETE SET OF POINTS & CONSTRUCT THE ENSUING COVARIANCE MATRIX
- EIGENVECTORS OF THE COVARIANCE MATRIX AS A BASIS IN THE VECTOR SPACE SPANNED BY THE REPLICAS BY SINGULAR-VALUE DECOMPOSITION
- NUMBER OF DOMINANT EIGENVECTORS SIMILAR TO NUMBER OF REPLICAS $\Rightarrow$ ACCURATE REPRESENTATION

TOOLS II
NONGAUSSIAN BEHAVIOUR

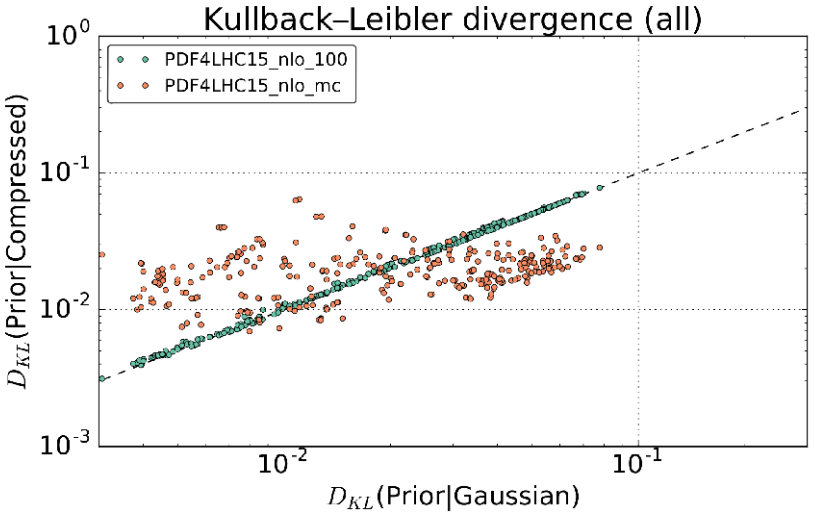
MONTE CARLO COMPARED TO HESSIAN

CMS $W + c$ production



- DEVIATION FROM GAUSSIANITY E.G. AT LARGE x DUE TO LARGE UNCERTAINTY + POSITIVITY BOUNDS
  $\Rightarrow$ RELEVANT FOR SEARCHES
- CANNOT BE REPRODUCED IN HESSIAN FRAMEWORK
- WELL REPRODUCED BY COMPRESSED MC

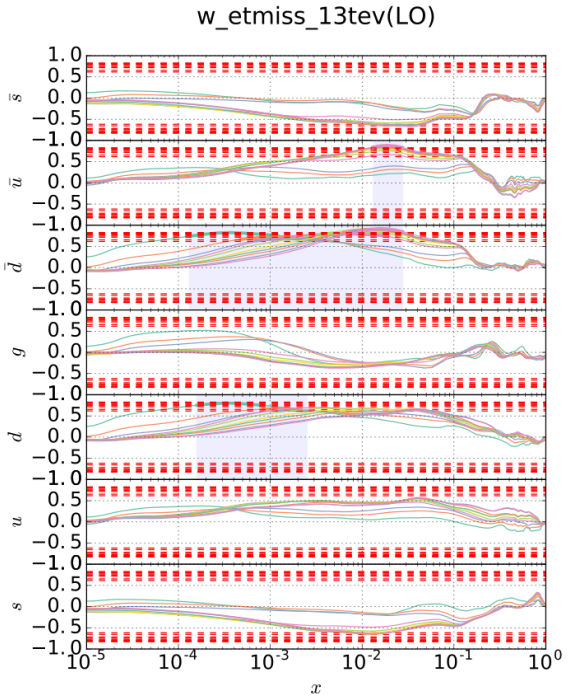
- DEFINE KULLBACK-LEIBLER DIVERGENCE
  $D_{\mathrm{KL}} = \int_{-\infty}^{\infty} P(x) \frac{\ln P(x)}{\ln Q(x)}\, dx$
  BETWEEN A PRIOR P AND ITS REPRESENTATION Q
- D_{KL} BETWEEN PRIOR AND HESSIAN DEPENDS ON DEGREE OF GAUSSIANITY
- D_{KL} BETWEEN PRIOR AND COMPRESSED MC DOES NOT

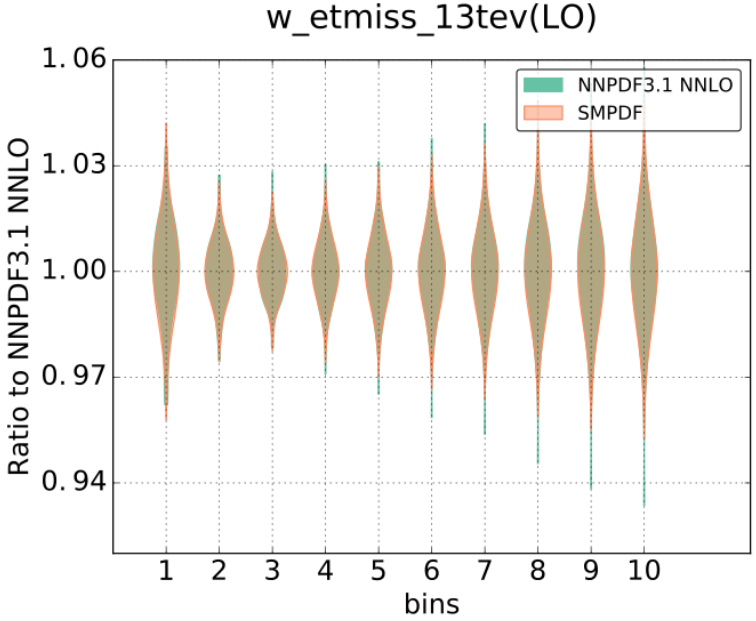


CAN (A) GAUGE WHEN MC IS MORE ADVANTAGEOUS THAN HESSIAN;
(B) ASSESS THE ACCURACY OF COMPRESSION

TOOLS III
OPTIMIZED PDFS: SMPDF

- OLD ASPIRATION: PDFS OPTIMIZED TO PROCESSES (Pumplin 2009)
- SELECT SUBSET OF THE COVARIANCE MATRIX CORRELATED TO A GIVEN SET OF PROCESSES
- PERFORM SVD ON THE REDUCED COVARIANCE MATRIX, SELECT DOMINANT EIGENVECTOR, PROJECT OUT ORTHOGONAL SUBSPACE
- ITERATE UNTIL DESIRED ACCURACY REACHED
- CAN ADD PROCESSES TO GIVEN SET; CAN COMBINE DIFFERENT OPTIMIZED SETS
- WEB INTERFACE AVAILABLE





(Carrazza, SF, Kassabov, Rojo, 2016)

- EG ggH, $Hb\bar{b}$, W $E_T^{\rm miss}$ $\Rightarrow$ 11 EIGENVECTORS
- STUDY CORRELATIONS OF PDFS TO DATA AND AMONG THEMSELVES!