



PARTON DISTRIBUTIONS

OR

THE ART OF SOLVING ILL-POSED PROBLEMS

STEFANO FORTE UNIVERSITÀ DI MILANO & INFN



UNIVERSITÀ DEGLI STUDI DI MILANO DIPARTIMENTO DI FISICA



1ST COFI WORKSHOP

SAN JUAN, PR, JULY 17, 2019

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SUMMARY

PDFs NOW

- FROM PDF4LHC15 TO NEW GENERATION SETS
- THE IMPACT OF LHC DATA
- RESOLVING ISUES WITH DATA: STRANGENESS & CHARM
- DATA VS. METHODOLOGY

FITTING THE METHODOLOGY

- DATASET OPTIMIZATION?
- MACHINE LEARNING PDFs
- HYPEROPTIMIZATION
- WHAT IS PROPER LEARNING?

THEORY UNCERTAINTIES

- PDF THEORY ERRORS?
- THE THEORY COVARIANCE MATRIX
- SCALE VARIATION AND ITS VALIDATION
- PDFs with theory errors and their impact





THE STATE OF THE ART

CONTEMPORARY PDF TIMELINE (ONLY PUBLISHED GLOBAL)

	20	08	20	09	20	10	2011	20	12	20	13	20	14	2015	20	017
SET	CTEQ6.6 Q	NNPDF1.0	MSTW (01)	ABKM09	NNPDF2.00	(NLO)	NNPDF2.1 (NNLO)	ABM11 (02)	NNPDF2.30	CT10 (NNLO) Q	ABM12 (10)	の NNPDF3.0つ	MMHT (12)	CT14 06	ABMP16 01	NNPDF3.10
F. T. DIS ZEUS+H1-HI COMB. HI ZEUS+H1-HII HERA JETS	v v x x	v v x x	v x x	v v x x	v v x	× × ×	v v some	v v x x	V V V X	v v some	v v v x		× × ×	× × ×	v v v v	
F. T. DY	×	×	 	×	×	×	×	×	×	×	×	×	/	×	×	×
TEV W+Z LHC W+Z	v ×	× × ×	v ×	× ×	2 2 X	v x	~ ~ X	× ×	~ ~ ~	v x	× some	2 2 2	2 2 2	2 2 2	× some	2 2 2
TEV JETS LHC JETS	× ×	× ×	✓ ×	× ×	× ×	× ×	x x	✓ ×	<i>v</i> <i>v</i>	✓ ×	x x	~ ~	<i>v</i> <i>v</i>	v v	x x	<i>v</i> <i>v</i>
TOP TOTAL SINGLE TOP TOTAL TOP DIFFERENTIAL	× × ×	× × ×	× × ×	× × ×	× × ×	× × ×	× × ×	× × ×	X X X	X X X	✓ × ×	✓ × ×	× × ×	× × ×	v v ×	× ×
$ \begin{array}{c} W \ p_T \\ W+C \\ Z \ p_T \end{array} $	× × ×	x x x	x x x	x x x	x x x	X X X	X X X	X X X	x x x	x x x	X X X	~ ~ X	X X X	X X X	× × ×	X X

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: (mrst2004ged), NNPDF2.3QED (08/13), NNPDF3.0QED (06/16), NNPDF3.1LUXQED (12/17)



NO QUALITATIVE DIFFERENCE BETWEEN NLO AND NNLO

- 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

DATASET WIDENING NNPDF3.0 vs NNPDF3.1

Kinematic coverage



NEW DATA: (BLACK EDGE)

- HERA COMBINED F_2^b
- D0 W LEPTON ASYMMETRY
- ATLAS W, Z 2011, HIGH & LOW MASS DY 2011; CMS W[±] 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 PDF UNCERTAINTIES IN DETAIL: NNPDF3.0 (NNLO)



- 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

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





- 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



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



LESSONS:

- 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 \rightarrow CT18Z

- ATLAS W and Z 7TeV rapidity included
- CHARM MASS INCREASED
- x-dependent factorization scale



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

• CHARM SHOULD NOT DEPEND STRONGLY ON CHARM MASS



• ITS SHAPE SHOULD NOT BE DETERMINED BY FIRST-ORDER MATCHING (NO HIGHER NONTRIVIAL ORDERS KNOWN)

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



- QUARK LUMI AFFECTED BECAUSE OF CHARM SUPPRESSION AT MEDIUM-x
- FLAVOR DECOMPOSITION ALTERED
- UNCERTAINTIES ON LIGHT QUARKS NOT SIGNIFICANTLY INCREASED



• 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



OPTIMIZING THE METHODOLOGY

$\begin{array}{c} \text{DATA} \Rightarrow \text{THEORY ISSUES} \\ \text{VISUALIZATION TOOLS} \\ \text{TRACING THE IMPACT OF DATA} \end{array}$

- DETERMINE THE SHIFT IN DATAPOINTS INDUCED BY CHANGES IN PDF
- CT14: 28 HESSIAN PARAMETER VARIATIONS
- VISUALIZE SHIFT VECTORS FOR 4000 datapoints
 - BY PCA
 - BY TOUR



LESSONS FROM THE PAST: TWENTY YEARS BACK....

- NO PDF UNCERTAINTIES
- UNCERTAINTY \Leftrightarrow PDF SET VARIATION
- METOHDOLOGY \leftrightarrow AGREEMENT WITH DATA

CDF JETS

GLUON UNCERTAINTY



FITTING THE METHODOLOGY THE N3FIT PROJECT



(Carrazza, Cruz-Martinez, 2019)

- PYTHON-BASED KERAS + TENSORFLOW FRAMEWORK
- EACH BLOCK INDEPENDENT LAYER
- CAN VARY ALL ASPECT OF METHODOLOGY
- GRADIENT DESCENT DETERMINISTIC MINIMIZATION
- ONE SINGLE NEURAL NET FOR ALL PDFS



- SCAN PARAMETER SPACE
- OPTIMIZE FIGURE OF MERIT
- BAYESIAN UPDATING

FITTING THE METHODOLOGY OVERLEARNING VS. PROPER LEARNING



- CROSS-VALIDATION \Rightarrow RANDOMLY DIVIDE DATA INTO TRAINING AND VALIDATION SETS
- MINIMIZE ON TRAINING; OPTIMIZE ON VALIDATION
- NO OVERLEARNING \Rightarrow NOISE NOT LEARNT
- OVERFITTING $\Rightarrow \chi^2_{\text{train}} << \chi^2_{\text{valid}}$!! & WIGGLY PDFS
- CORRELATIONS BETWEEN DATA IN A SET

PROPER LEARNING VS. OVERLEARNING THE TEST SET METHOD

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



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

FITTING THE METHODOLOGY WHAT IS "PROPER LEARNING"?

- FORECASTNG AN UNKNOWN TRUTH \Rightarrow WHAT IS "OPTIMAL"?
- ARE STATISTICAL PROPERTIES OF THE ENSEMBLE RELEVANT?
- SHOULD THEORY PREJUDICE PLAY A ROLE?
- CLOSURE TESTING?
- REINFORCEMENT LEARNING? \Rightarrow STAY TUNED!

MENU V 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

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THEORY UNCERTAINTIES

MISSING HIGHER ORDER UNCERTAINTY ON FACTORIZED OBSERVABLES

 $\sigma = \hat{\sigma} \otimes f \otimes f$ schematically

 $\sigma(M_w^2) = \hat{\sigma}(M_w^2) \left[\Gamma(M_w^2, Q^2) F_2(Q^2) \right]^2; \ \Gamma(M_w^2, Q^2) = \exp \int_{Q^2}^{M_W^2} \frac{d\alpha}{\beta(\alpha)} \gamma(\alpha)$

- HADRONIC XSECT= PARTONIC XSEC TIMES PDFs (CONVOLUTION)
- PDFs Are a proxy for another process (DIS)
- MUST EVOLVE BETWEEN TWO PROCESSES

SOURCES OF MHOU UNCERTAINTY

- MHOU IN THE "DRELL-YAN" XSECT \Rightarrow STANDARD SCALE VARN.
- MHOU IN THE STRUCTURE FUNCTIONS \Rightarrow TH. UNCERTAINTY ON PDFs (1)
- MHOU IN THE EVOLUTION \Rightarrow TH. UNCERTAINTY ON PDFs (2)



- TODAY: NLO PDF & MHOU UNCERTAINTIES COMPARABLE
- NEAR FUTURE: SHOULD WE WORRY ABOUT NNLO MHOU?

THE MISSING HIGHER ORDER UNCERTAINTY ON PDFS CAN WE ESTIMATE IT? SCALE VARIATION IN PDF FITTING

NAIVE IDEA FOR PDF MHOU ESTIMATE

- PERFORM FIT WITH VARIOUS SCALE CHOICES
- TAKE ENVELOPE OF RESULTS
- 7-POINT \Rightarrow OK!; 9-POINT \Rightarrow UNSTABLE!
- **RESULTS DEPEND STRONGLY ON THE CHOICE OF ENVELOPE**



THE THEORY COVARIANCE MATRIX

(NNPDF, 2019)

• ASSOCIATE MHOU TO NUISANCE PARAMETER \Rightarrow THEORY COVARIANCE MATRIX S_{ii}

•
$$S_{ij} = \frac{1}{N} \sum_{k} \left(T_i^{(k)} - T_i^{(0)} \right) \left(T_j^{(k)} - T_j^{(0)} \right)$$

 $\left(T_i^{(k)} - T_i^{(0)} \right)$: k-th shift of *i*-th datapoint about central prediction $T_i^{(0)}$

• SHIFT: GUESS FOR POSSIBLE MHO TERMS \Rightarrow SCALE VARIATION



EXPERIMENTS AND PROCESSES

Datasets

Process Type

DIS NC

DIS CC

DY

JET TOP

- CLASSIFY DATA INTO PROCESSES
- PICK A SET OF SCALE VARIATIONS
- DECIDE HOW TO CORRELATE SCALE VARIATION BETWEEN DIFFERENT PROCESSES •
- **RENORMALIZATION** \Rightarrow **MATRIX ELEMENT**; FACTORIZATION \Rightarrow EVOLUTION

THE THEORY COVARIANCE MATRIX: FACTORIZATION VS RENORMALIZATION SCALE

Scale	MHOU	'Traditional' name	'Modern' name[PDG]
$\begin{vmatrix} \mu_r \\ \mu_f \\ \widetilde{\mu} \end{vmatrix}$	in hard xsec		renormalization scale
	in PDF evolution	renormalization scale	factorization scale
	in physical xsec	factorization scale	scale of the process

- Ren: $\mu_r \Rightarrow$ MHOU in hard cross section
- Fact: $\mu_f \Rightarrow$ MHOU IN ANOMALOUS DIMENSION

PRESCRIPTIONS

- **3 POINT**: $\tilde{\mu} = \mu_r = \mu_f$ uncorrelated between processes
- **5 POINT**, **5 POINT**, **9 POINT**: $\mu_r \ \mu_f$ varied independently, μ_r uncorrelated, μ_f correlated
- 7 point: $\widetilde{\mu}$ added to 5 point



THE THEORY COVARIANCE MATRIX: CORRELATIONS

- INDEPENDENT NUISANCE PARAMETERS \Rightarrow TH. AND EXP. ERRORS COMBINE IN QUADRATURE $\chi^2 = \sum_{i,j=1}^{N_{\text{dat}}} \left(D_i T_i^{(0)} \right) [S+C]_{ij}^{-1} \left(D_i T_i^{(0)} \right)$
- REN. SCALE ⇒ CORRELATIONS INDUCED BETWEEN EXPERIMENTALLY UNRELATED MEASUREMENTS OF SAME PROCESS
- FACT. SCALE \Rightarrow CORRELATIONS INDUCED BETWEEN DIFFERENT PROCESSES



EXPERIMENT

THE COVARIANCE MATRIX

THEORY (9 PT)

Theory Covariance matrix (9 pt)



THE THEORY COVARIANCE MATRIX: VALIDATION

- COMPARE NLO THEORY COVMAT TO OBSERVED NLO-NNLO SHIFTS
- DETERMINE EIGENVECTORS e_i of COVMAT $\Rightarrow 28$ evecs for 9pt, five processes
- Determine vector of shifts δ
- DETERMINE PROJECTION OF δ IN SUBSPACE SPANNED BY e_i : IS IT CONTAINED IN IT?
- DETERMINE SIZE δ_i OF PROJECTIONS OF δ ALONG e_i : ARE THEY OF COMPARABLE SIZE?







- ALL PRESCRIPTIONS BUT 3-PT PERFORM WELL
- ANGLE SCALES WITH NUMBER OF DATAPOINTS \Rightarrow MORE POINTS, WORSE AGREEMENT

•	ANGLE	DOMINATED	BY	WORSE	PROCESS
---	-------	-----------	----	-------	---------

PRESCRIPTION	Nauk	θ	PRESCRIPTION			θ		
				DIS NC	DIS CC	DY	JET	ТОР
3-рт	6	52 ⁰	3-pt	54^{O}	36 ⁰	39 ⁰	24 ⁰	12 ⁰
5-рт	8	33 ⁰	5-рт	39 ⁰	21 ⁰	25^{O}	17 ⁰	11 ⁰
<u>5</u> -pt	12	31 ⁰	<u>5</u> -pt	38 ⁰	17 ⁰	23 ⁰	22 ⁰	10 ⁰
7-pt	14	29 ⁰	7-pt	35 ⁰	17 ⁰	22 ⁰	16 ⁰	3 ⁰
9-PT	28	26 ⁰	9-pt	32^{O}	16 ⁰	22 ⁰	14 ⁰	3 ⁰

THE THEORY COVARIANCE MATRIX: VISUALIZING PROCESS IMPACT

- PROJECT THE SHIFT VECTOR δ on each eigenvector
- LOOK AT THE INDIVIDUAL $\sim 3000 \text{ components}$
- GROUP POINTS BY PROCESS
- RELATION BETWEEN SCALE VARIATION EIGENVECTORS & PROCESSES

projection of the shift vector along the four dominant eigenvectors



EQUALLY PRECISE BUT MORE ACCURATE RESULT!

CENTRAL VALUE MOVES TOWARDS KNOWN NNLO

- EXTRAPOLATION REGION: PDF UNCERTAINTY SIGNIFICANTLY INCREASES
- DATA REGION: PDF UNCERTAINTY ALMOST UNCHANGED
- RELATIVE ERROR ϕ ON PREDICTION DOES NOT CHANGE
- FIT QUALITY χ^2 IMPROVES

	С	$C + S^{(3\mathrm{pt})}$	$C + S^{(9\mathrm{pt})}$
χ^2	1.139	1.139	1.109
ϕ	0.314	0.310	0.315



EQUALLY PRECISE BUT MORE ACCURATE RESULT!

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χ^2	1.139	1.139	1.109
ϕ	0.314	0.310	0.315





USAGE: JUST COMPUTE PDF ERROR AS USUAL & COMBINE WITH MHOU ON HARD MATRIX ELEMENT COMPUTED WITH YOUR PREFERRED RECIPE

- GLUON FUSION, TOP
 - NO EFFECT ON CENTRAL VALUE
 - VISIBLE INCREASE OF UNCERTAINTIE
- VBF
 - MODERATE EFFECT ON UNCERTAINTIES
 - VISIBLE SHIFT OF CENTRAL VALUES

OUTLOOK

SUMMARY

- BETTER DATA ⇔ BETTER THEORY AND BETTER METHODOLOGY
- CAN WE REDUCE ARBITRARINESS IN PDF METHODOLOGY?
- CAN WE ASSESS ACCURATELY OUR THEORETICAL IGNORANCE?







PDF UNCERTAINTIES: TOLERANCE (MMHT-CT)

- (MSTW/MMHT) FOR EACH EIGENVECTOR IN PARAMETER SPACE DETERMINE CONFIDENCE LIMIT FOR THE DISTRIBUTION OF BEST-FITS OF EACH EXPERIMENT
- Rescale $\Delta\chi^2 = T$ interval such that correct confidence intervals are reproduced
- SIMILAR PROCEDURE ADOPTED BY CTEQ

WHAT ABOUT NNPDF?

$\frac{MC}{} \Leftrightarrow \frac{HESSIAN}{PDF}$ two different representations of PDF uncertainties

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





- 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 REPLI-CAS BY SINGULAR-VALUE DECOMPOSITION
- NUMBER OF DOMINANT EIGENVECTORS SIMILAR TO NUMBER OF REPLICAS \Rightarrow ACCURATE REPRESENTATION

WHAT IS THE NNPDF "TOLERANCE"?

FINITE-SIZE EFFECTS $\Delta \chi^2 = T^2$ VS NUMBER OF REPLICAS

- PERFORM HESSIAN CONVERSION OF NNLO NNPDF3.1 PDFs 50 or 100 eigenvectors
- DETERMINE χ^2 Along Each eigenvector direction
- FIT A QUARTIC POLYNOMIAL
- STUDY DEPENDENCE ON NONGAUSSIANITY, NUMBER OF REPLICAS, NUMBER OF EIGENVECTORS,...



(Talon, MS thesis, 2019)

- NO SIGNIFICANT NONGAUSSIANITIY, DEVIATION FROM PARABOLIC, . . .
- 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?



(Carrazza, Latorre, Kassabov, Rojo, 2015)

- START WITH LARGE REPLICA SAMPLE
- SELECT (BY GENETIC ALGORITHM) SUBSET OF REPLICAS \Rightarrow STATISTICAL FEATURES OPTIMIZED TO PRIOR
- FOR ALL PDFS ON A GRID OF POINTS MINIMIZE DIFFERENCE OF FIRST FOUR MOMENTS, CORRELATIONS; OUTPUT OF KOLMOGOROV-SMIRNOV TEST (NUMBER OF REPLICAS BETWEEN MEAN AND σ , 2σ , INFINITY)
- 50 COMPRESSED REPLICA REPRODUCE 1000 REPLICA SET TO PRECENT ACCURACY

GAN REPLICA GENERATION

- 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



- 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



(Carrazza, Rabemananjara, preliminary)

 ● 1D GAN: REPRODUCE THE INFORMATION IN THE UNDERLYING REPLICA SET, BUT NO GAIN (WIGGLY REPLICAS)
 ⇒ 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 ⇒ REDUCE THE NUMBER OF INPUT REPLICAS W/O INFORMATION LOSS





PDFS WITH THEORY UNCERTAINTIES

- Results mildly dep. On prescription \Rightarrow 3pt closer to result w/o theory uncertainty
- "UNSTABLE" SCALE VARIATIONS \Rightarrow NO IMPACT ON FIT
- 7PT ENVELOPE RATHER MORE CONSERVATIVE ENVELOPE DOES NOT INCLUDE EXP. UNCERTAINTY





EXPERIMENT



EXP+THEORY ($\overline{5}$ PT)



EXP+THEORY (7 PT)

DISCC



EXP+THEORY (9 PT)



CORRELATION MATRICES EXP+THEORY (3 PT) EXP+THEORY (5 PT)

DIS N

DY

JETS

F

TOP

OIS NC

Experimental + Theory Correlation Matrix (3 pt)

I NI

50

IET TOP

DIS CC



STATISTICAL INDICATORS

PRC	OCESS	n_{dat}			$\chi^2/n_{ m d}$	lat in the NNPDF NLO	73.1 GLOBAL FITS		NNLO
		uat	C	$C + S^{(9p)}$	t) $C + S^{(7\text{pt})}$	$C + S^{(3pt)}$	t) $C + S_{\text{fit}}^{(9\text{pt})}$	$C + S_{\text{sampl}}^{(9\text{pt})}$	C
DIS DIS	S NC S CC	1593 552	1.08 1.0	88 1.079 12 0.928	1.086 0.933	$1.095 \\ 0.960$	1.081 0.929	1.227 1.036	1.084 1.079
DY JET TOI	rs P	484 164 26	1.48 0.90 1.20	86 1.447 07 0.839 60 1.012	1.485 0.858 1.016	1.483 0.901 1.077	1.461 0.848 1.001	1.434 0.911 1.264	1.231 0.950 1.068
Тот	AL	2819	1.13	39 1.109	1.129	1.139	1.113	1.217	1.105
	Proce	ESS	C	$C + S^{(9\mathrm{pt})}$	ϕ in the Γ $C+S^{(7\mathrm{pt})}$	NNPDF3.1 GLOBA NLO $C + S^{(3pt)}$	L FITS $C+S_{\mathrm{fit}}^{(9\mathrm{pt})}$	$C + S_{\text{sampl}}^{(9\text{pt})}$ N	NLO C
	DIS N		266	0.000	0.969	0.001		1 107	0.05
	DIS C	C C).389	0.268	0.367	0.261 0.391	0.261 0.369	0.502	.305 .471
	DIS C DY JETS TOP).389).361).295).375	0.268 0.376 0.343 0.312 0.352	0.262 0.367 0.340 0.279 0.318	0.261 0.391 0.358 0.291 0.331	0.261 0.369 0.349 0.298 0.319	1.137 0 0.502 0 0.603 0 0.461 0 0.612 0	.305 .471 .380 .392 .363

- MILD PRESCRIPTION DEPENDENCE
- COVMAT ONLY IN FITTING \Rightarrow SAME CENTRAL VALUE, REDUCED UNCERTAINTY TH COVMAT RESOLVES TENSION



PDF THEORY ERROR AS A FIT UNCERTAINTY

• PDFs are determined by maximizing the likelihood

$$P = N \exp - \left(\frac{d-t}{2\sigma_{exp}^2}\right)$$

d, t are really vectors and $1/\sigma^2$ the inverse covariance matrix

• CAN VIEW THIS AS THE PROBABILITY OF THE THEORY t BEING CORRECT GIVEN DATA d, WHICH BY BAYES IS

 $P(t|d) \propto P(d|t)P(t)$

- IF THEORY WAS KNOWN EXACTLY, THEN $P(t) = \delta(t t^{\text{exact}})$
- IN ACTUAL FACT ONLY SOME PERTURBATIVE RESULT t_p is exactly known so $t^{\text{exact}} = t_p + \Delta_p$, where Δ_p includes MHO
- Assuming Δ to be Gaussianly distributed, with uncertainty $\sigma_{\rm th}$ and integrating out

$$P = N \exp\left[rac{d - t_p}{2\left(\sigma_{exp}^2 + \sigma_{th}^2
ight)}
ight]$$

- THEORETICAL UNCERTAINTY ADDED IN QUADRATURE, PROPAGATES INTO PDF UNCERTAINTY UPON MINIMIZATION
- SCALE VARIATION FOR EACH DATA POINT \Rightarrow EIGENVECTOR OF COVARIANCE MATRIX (NUISANCE PARM.)