CAPIRE LA STRUTTURA DEL PROTONE

CON

L'INTELLIGENZA ARTIFICIALE

STEFANO FORTE

UNIVERSITÀ DI MILANO & INFN

UNIVERSITÀ DEGLI STUDI DI MILANO

DIPARTIMENTO DI FISICA

Istituto Nazionale di Fisica Nucleare

SEMINARIO PLS

MILANO, 23 FEBBRAIO 2018

Ma non è una "particella elementare"?

The history of physics shows that whenever experimental techniques advance to an extent that matter, as then known, can be analyzed into "elemental" parts, newer and more powerful studies subsequently show that the "elementary particles" have a structure themselves

Robert Hofstadter, 1961 Nobel Lecture

Rutherford, 1919 → Misura del raggio del nucleo

R. Hofstadter, 1953 → Misura del raggio del protone

Come si fa la "radiografia" di una particella?

- SONDA CON LUNGHEZZA D'ONDA $<$ DIMENSIONI DELLA PARTICELLA

  Esempio: reticoli cristallini $\rightarrow \lambda \sim 10^{-8} cm \rightarrow$ raggi X

- MISURA DELLA "LUCE DIFFUSA" $\Rightarrow$ SEZIONE D'URTO

  Numero di particelle diffuse per unità di flusso incidente

CARICA PUNTIFORME: urto coulombiano

distanza minima b proiettile–bersaglio vs. angolo d'urto θ

$$1 + \frac{1}{\sin \theta/2} = K q q' \frac{b}{k}$$

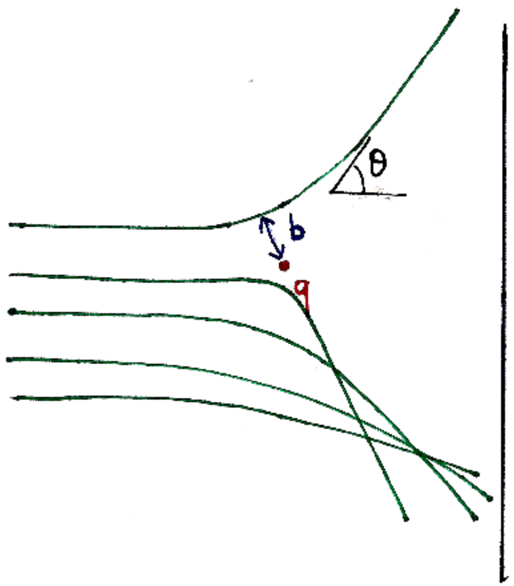
$k = \frac{\hbar c}{\lambda}$: IMPULSO; q E q': CARICHE; K: COST. NUMERICA

MAGGIORE AVVICINAMENTO $\Leftrightarrow$ DIFFUSIONE A GRANDE ANGOLO

MINORE AVVICINAMENTO $\Leftrightarrow$ DIFFUSIONE A PICCOLO ANGOLO

MAGGIORE ENERGIA (IMPULSO) $\Leftrightarrow$ MAGGIORE AVVICINAMENTO

MINORE ENERGIA (IMPULSO) $\Leftrightarrow$ MINORE AVVICINAMENTO



LA FORMA DEL PROTONE

CARICA NON PUNTIFORME:
MINORE DISTANZA $b \rightarrow$ IL PROIETTILE "VEDE" MENO CARICA q
$\rightarrow$ MINORE DEFLESSIONE
N. DI PARTICELLE (SEZ. D'URTO) σ RIDOTTO: FATTORE DI FORMA $F^2(Q^2)$
ANGOLO $\theta \Leftrightarrow$ IMPULSO TRASFERITO $Q^2 \equiv -q^2 \approx 2p^2(1-\cos\theta)$, $q \equiv p - p'$:

SEZIONE D'URTO

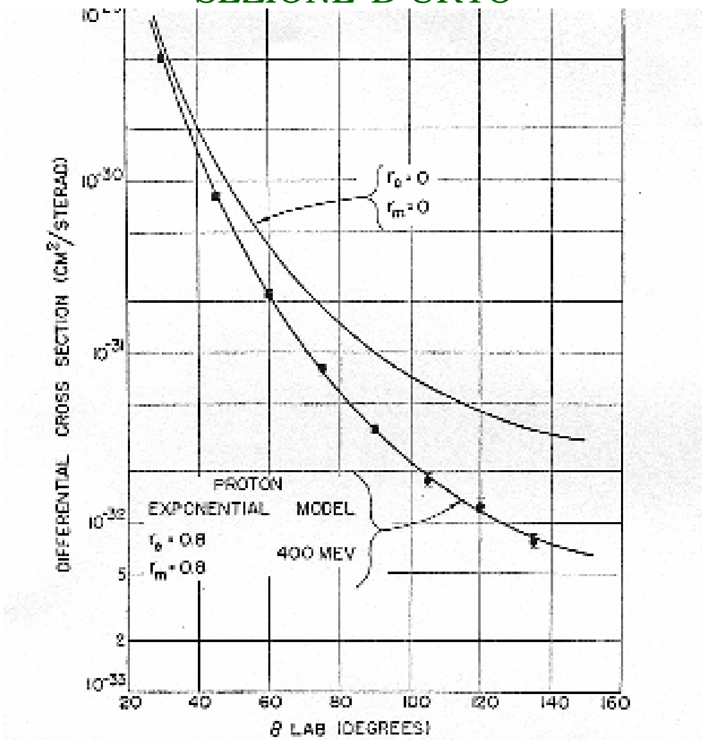


FIG. 26. Typical angular distribution for elastic scattering of 400-Mev electrons against protons. The solid line is a theoretical curve for a proton of finite extent. The model providing the theoretical curve is an exponential with rms radii$=0.80\times10^{-13}$ cm.

$$\frac{d\sigma}{dq^2} = F^2(q^2)\frac{d\sigma_0}{dq^2}$$

FATT. DI FORMA (HOFSTADTER, 1956)

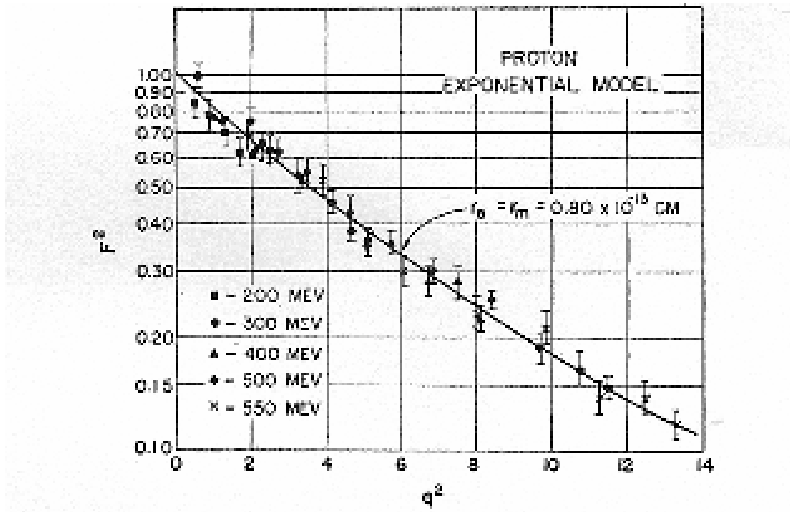


FIG. 27. The square of the form factor plotted against q^2. q^2 is given in units of 10^{-26} cm². The solid line is calculated for the exponential model with rms radii$=0.80\times10^{-13}$ cm.

DECRESCITA $\leftrightarrow$ RAGGIO DEL PROTONE (R = raggio): $F(q^2) \sim \exp(-R^2q^2)$

SEMPRE PIÙ IN PROFONDITÀ

STRUTTURA DEI COSTITUENTI $\Rightarrow$ URTO INELASTICO

- URTO INELASTICO $\Rightarrow$ IL PROTONE SI SPEZZA
- URTO SUI COSTITUENTI $\Leftrightarrow$ RAGGIO DEI COSTITUENTI

CASO ELASTICO:

CASO INELASTICO:

SEMPRE PIÙ IN PROFONDITÀ

STRUTTURA DEI COSTITUENTI ⇒ URTO INELASTICO

- URTO INELASTICO ⇒ IL PROTONE SI SPEZZA
- URTO SUI COSTITUENTI ⇔ RAGGIO DEI COSTITUENTI

CASO ELASTICO:

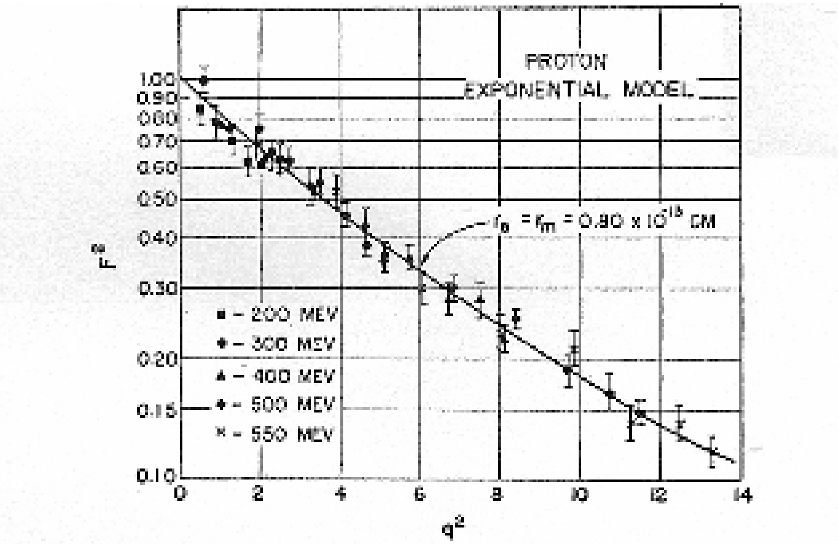
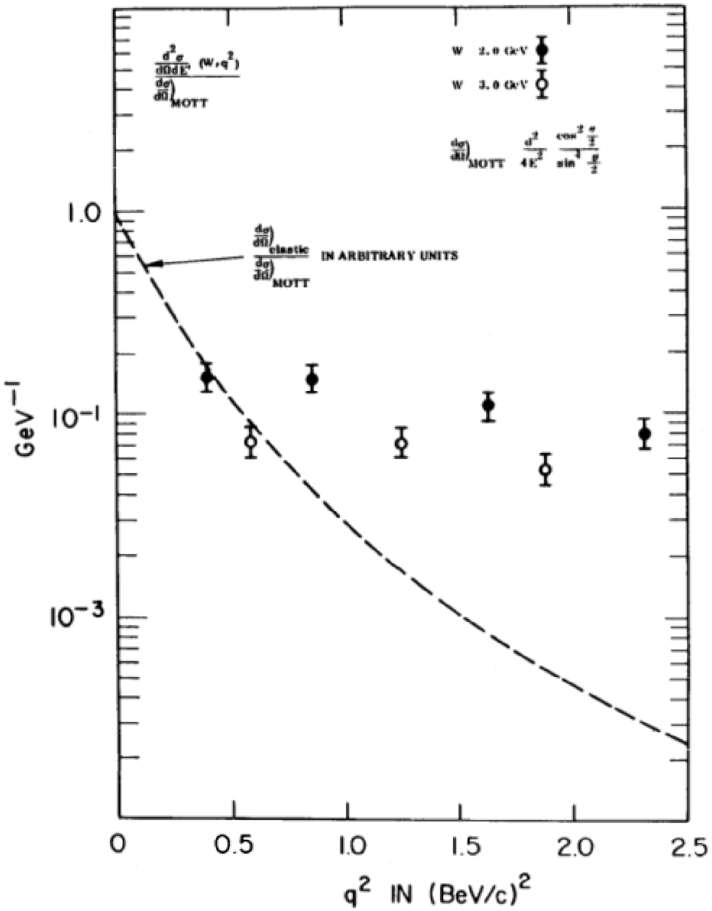


FIG. 27. The square of the form factor plotted against q^2. q^2 is given in units of 10^{-26} cm². The solid line is calculated for the exponential model with rms radii $=0.80\times10^{-13}$ cm.

CASO INELASTICO:



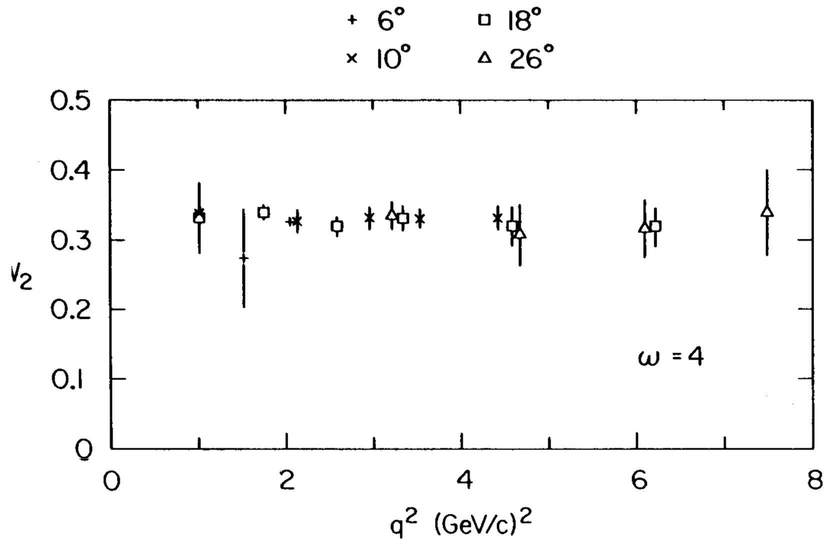
LA SEZ. D'URTO INELASTICA DECRESCE MOLTO LENTAMENTE CON L'ENERGIA

COSTITUENTI MOLTO PICCOLI DENTRO AL PROTONE?

SCALING (Feynman, Bjorken, 1969)

COSTITUENTI LIBERI, PUNTIFORMI, SENZA MASSA
IMPULSO $\hat{p}$ PROPORZIONALE ALL'IMPULSO DEL PROTONE p; $\hat{p} = xp$.

- x MISURABILE! $x = Q^2/(2p \cdot q)$
- FATTORE DI FORMA (FUNZ.DI STRUTTURA) A FISSO x INDIPENDENTE DA Q^2

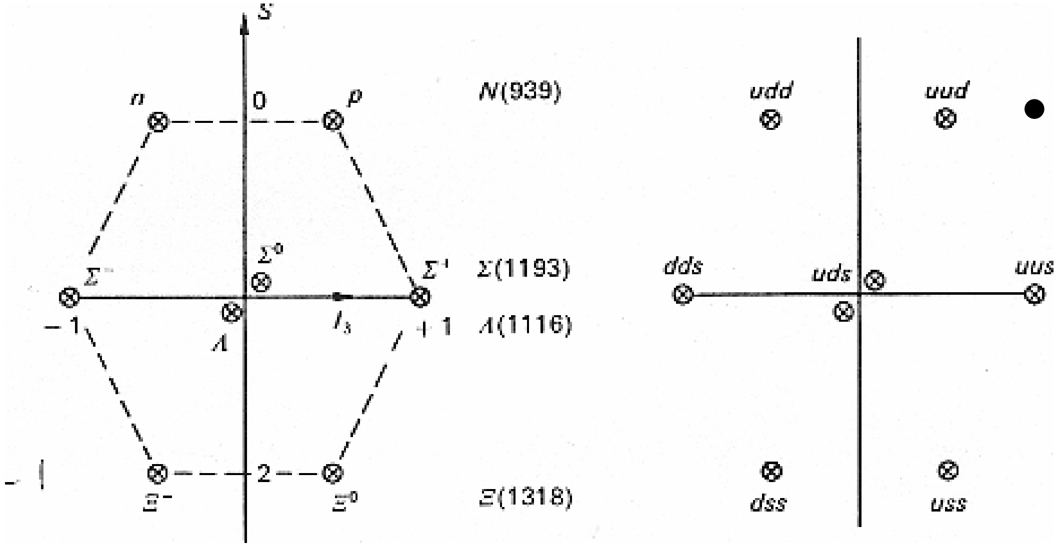


L'URTO INELASTICO "VEDE" COSTITUENTI PUNTIFORMI, SENZA MASSA, LIBERI.
SONO I QUARK?

Il protone è fatto di quark?

quark	u	d	s
I (isospin)	1/2	1/2	0
I_3 (isospin$_3$)	1/2	-1/2	0
Q (carica)	2/3	-1/3	-1/3
S (stranezza)	0	0	-1

antiquark	$\bar{u}$	$\bar{d}$	$\bar{s}$
I (isospin)	1/2	1/2	0
I_3 (isospin$_3$)	1/2	-1/2	0
Q (carica)	-2/3	1/3	1/3
S (stranezza)	0	0	1



PARTICELLE FORTEMENTE INTERAGENTI

- PROPRIETÀ STATICHE(CARICA, MASSE, MOMENTO MAGNETICO. . .) $\Rightarrow$ STATI LEGATI COSTITUENTI ELEMENTARI (QUARK) CON CARICA ELETTRICA FRAZIONARIA (M. Gell-Mann e G. Zweig, 1964)
- "BARIONI" (PROTONE, NEUTRONE) $\Rightarrow$ TRE QUARK
  MESONI (π) $\Rightarrow$ QUARK+ANTIQUARK.
- TRE QUARK "LEGGERI", MASSA CIRCA UGUALE:
  UP, DOWN, STRANGE

DOVE SONO I QUARK?

- QUARK LIBERI (= PARTICELLE CON CARICA ELETTRICA FRAZIONARIA) MAI TROVATI IN URTI DI ALTA ENERGIA, RAGGI COSMICI, NELLA MATERIA (ESPERIMENTI TIPO MILLIKAN).
- LIMITI TIPICI:
  - SEZ. D'URTO DI PRODUZIONE $\lesssim 10^{-10} \times$ SEZ. D'URTO P–P
  - FLUSSO COSMICO $\lesssim 10^{-14} \times$ FLUSSO DI MUONI;
  - DENSITÀ $\lesssim 10^{-20}$ QUARK/NUCLEONE.

Citation: C. Patrignani *et al.* (Particle Data Group), Chin. Phys. C, **40**, 100001 (2016) and 2017 update

t' (4^{th} Generation) Quark, Searches for

$m(t'(2/3)) > 782$ GeV, CL = 95% (neutral-current decays)
$m(t'(2/3)) > 700$ GeV, CL = 95% (charged-current decays)
$m(t'(5/3)) > 800$ GeV, CL = 95%

Free Quark Searches

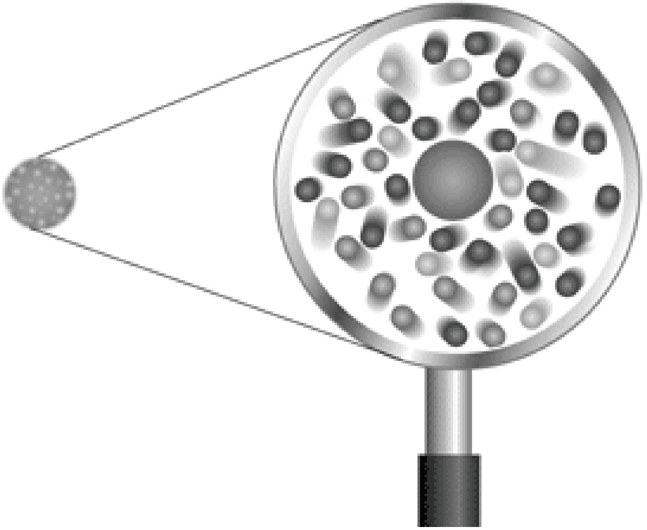
All searches since 1977 have had negative results.

CHE COSA C'E' DENTRO AL PROTONE?

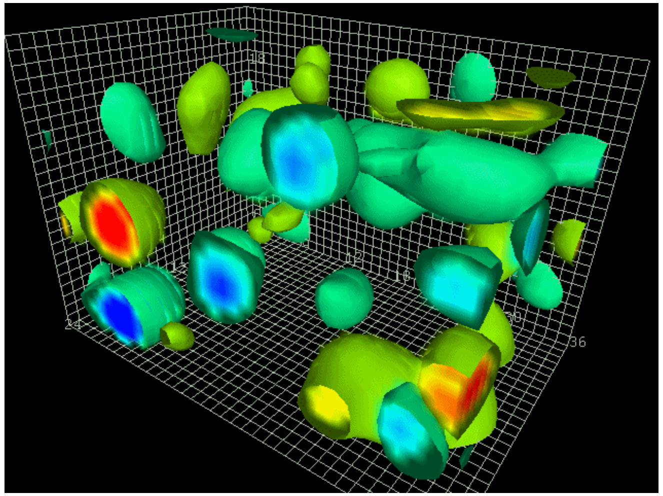
IL "VUOTO" QUANTISTICO

- INDETERMINAZIONE $\Rightarrow$ PARTICELLA CIRCONDATA DA UNA NUBE DI PARTICELLE VIRTUALI
- "VUOTO" QUANTISTICO $\Rightarrow$ MEZZO

PARTICELLA QUANTISTICA



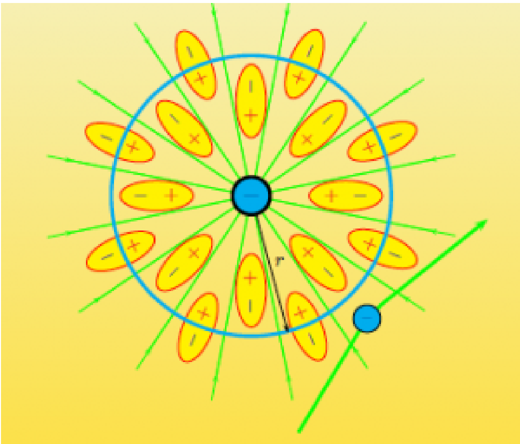
VUOTO QUANTISTICO



SCHERMAGGIO E ANTI-SCHERMAGGIO

QED

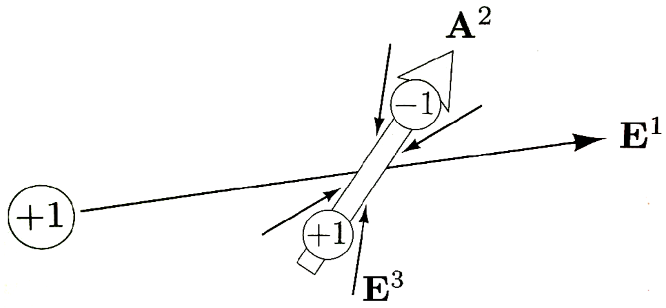
SCHERMAGGIO



- VUOTO $\Rightarrow$ “DIELETTRICO”
- CARICA ELETTRICA SCHERMATA A GRANDE DISTANZA
- CARICA ELETTRICA A CORTA DISTANZA $\Rightarrow$ CRESCE

QCD

ANTI-SCHERMAGGIO



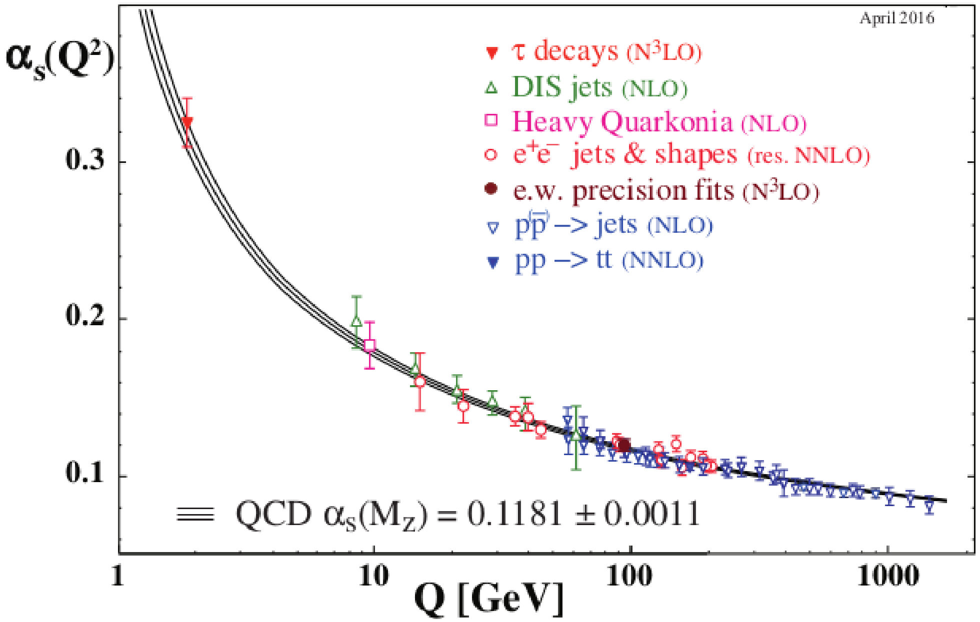
- QUARK $\Rightarrow$ CARICA “COLORATA”
- IL VUOTO RAFFORZA LA CARICA DI COLORE
- CARICA COLORATA A CORTA DISTANZA $\Rightarrow$ DECRESCE

Libertà asintotica

interazione forte $\Rightarrow$ forza fra quark "colorati" mediata da "gluoni"

- Bassa energia (grande distanza) $\leftrightarrow$ Quark confinati negli adroni
- Alta energia (piccola distanza) $\leftrightarrow$ Quark liberi

costante d'accoppiamento forte vs. energia

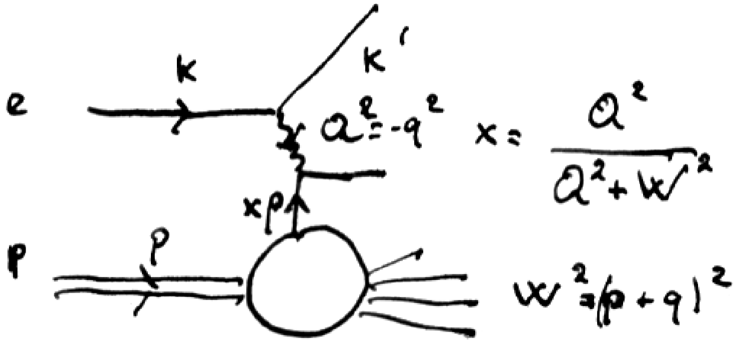


FACTORIZATION IN PERTURBATIVE QCD

DEEP-INELASTIC LEPTON-HADRON SCATTERING

PROBE THE PROTON WITH A SHORT-WAVELENGTH PHOTON:

QCD IS ASYMPTOTICALLY FREE, USE PERTURBATION THEORY:



$$\frac{d\sigma}{d\cos\theta\, dW^2} = \sum_i e_i^2 \frac{d\hat{\sigma}}{d\cos\theta\, dW^2} q_i(x(\theta, W^2)) + O\left(\frac{M^2}{Q^2}\right)$$

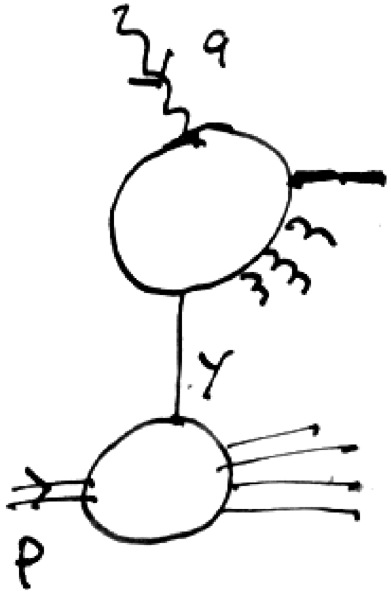
- AT FIRST PERTURBATIVE ORDER, SUM OF CONTRIBUTIONS FROM CHARGED CONSTITUENTS (QUARKS)
- MOMENTUM OF THE CONSTITUENT PROPORTIONAL TO PROTON MOMENTUM $\hat{p} = xp$
- "MOMENTUM FRACTION" x ENTIRELY FIXED BY KINEMATICS, BY Q^2 & W^2 (I.E. $\cos\theta$ & W^2)
- CROSS-SECTION PROPORTIONAL TO THE PROBABILITY $q_i(x)$ OF THE PHOTON STRIKING A QUARK OF THE i-TH FLAVOR OR ANTIFLAVOR WITH MOMENTUM $\hat{p} = xp$

PARTON MODEL; PARTON= STRUCK CONSTITUENT (QUARK):
$q_i(x) \Rightarrow$ PARTON DISTRIBUTION (PDF)

FACTORIZATION IN PERTURBATIVE QCD

DEEP-INELASTIC LEPTON-HADRON SCATTERING

TRUE TO ALL PERTURBATIVE ORDERS

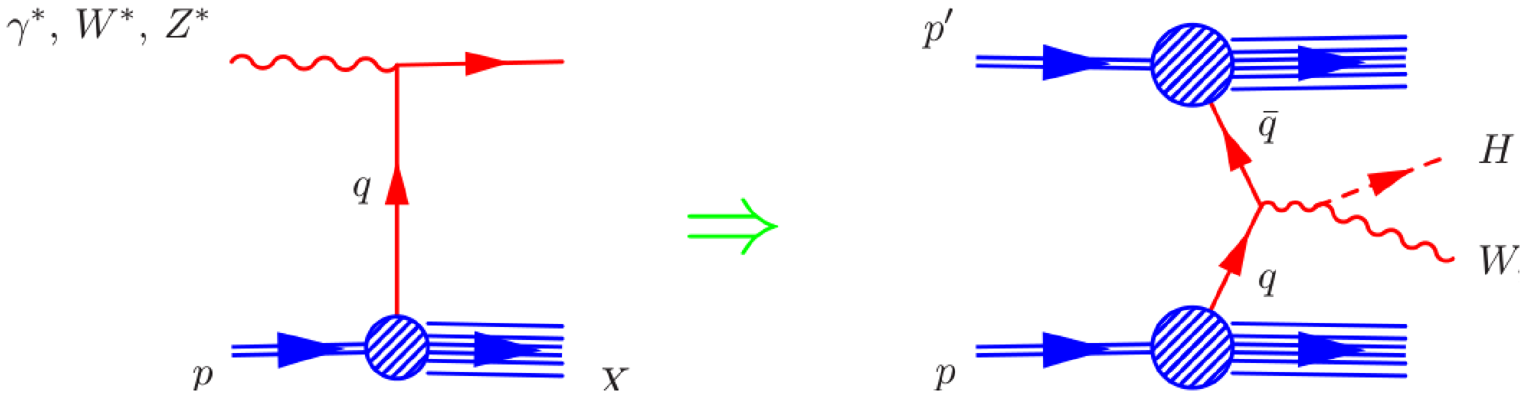


$$\frac{d\sigma}{d\cos\theta dW^2} = \sum_i e_i^2 \frac{d\hat{\sigma}}{d\cos\theta dW^2} \otimes q_i$$

- PROCESS FACTORIZES:
  PARTONIC PROCESS (QUARKS AND GLUONS) $\otimes$ PDF (QUARK, ANTIQUARK, GLUONS)
- PARTONIC PROCESS $\Rightarrow$ PERTURBATIVE; PDF $\Rightarrow$ PROTON W.F.
- PDF: PROBABILITY OF EXTRACTING PARTON WITH FRACTION x OF PROTON
- PDF DEPENDS ON SCALE (RESOLUTION) $\Rightarrow$ DEPENDENCE COMPUTABLE

FACTORIZATION

FROM ELECTRON-PROTON TO PROTON-PROTON



- FACTORIZATION: PDFS $\otimes$ PARTONIC CROSS-SECTION FOR SUB-PROCESS
- ONE PARTON PER HADRON: $\hat{p}_1 = x_a p_1$; $\hat{p}_2 = x_2 p_2$

FACTORIZATION FOR HADRONIC PROCESSES

THE PARTON LUMINOSITY

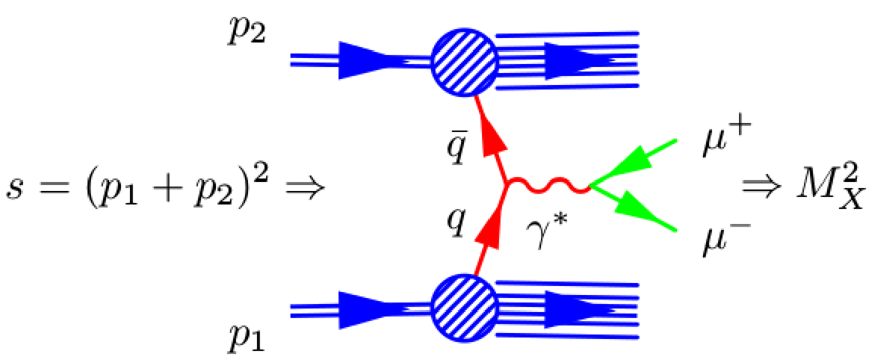
$$\sigma_X(s, M_X^2) = \sum_{a,b} \mathcal{L}_{ab} \otimes \hat{\sigma}_{ab}$$

$$\sigma_X(s, M_X^2) = \sum_{a,b} \int_{x_{\min}}^1 dx_1\, dx_2\, f_{a/h_1}(x_1) f_{b/h_2}(x_2) \hat{\sigma}_{q_a q_b \to X}\left(x_1 x_2 s, M_X^2\right)$$

- PARTON LUMINOSITY $\mathcal{L}_{ab}(\tau) = f_a \otimes f_b = \int_\tau^1 \frac{dx}{x} f_{a/h_1}(x) f_{b/h_2}(\tau/x)$
- PARTONIC CROSS SECTION $\hat{\sigma}_{q_a q_b \to X}$

EXAMPLE: THE DRELL-YAN PROCESS

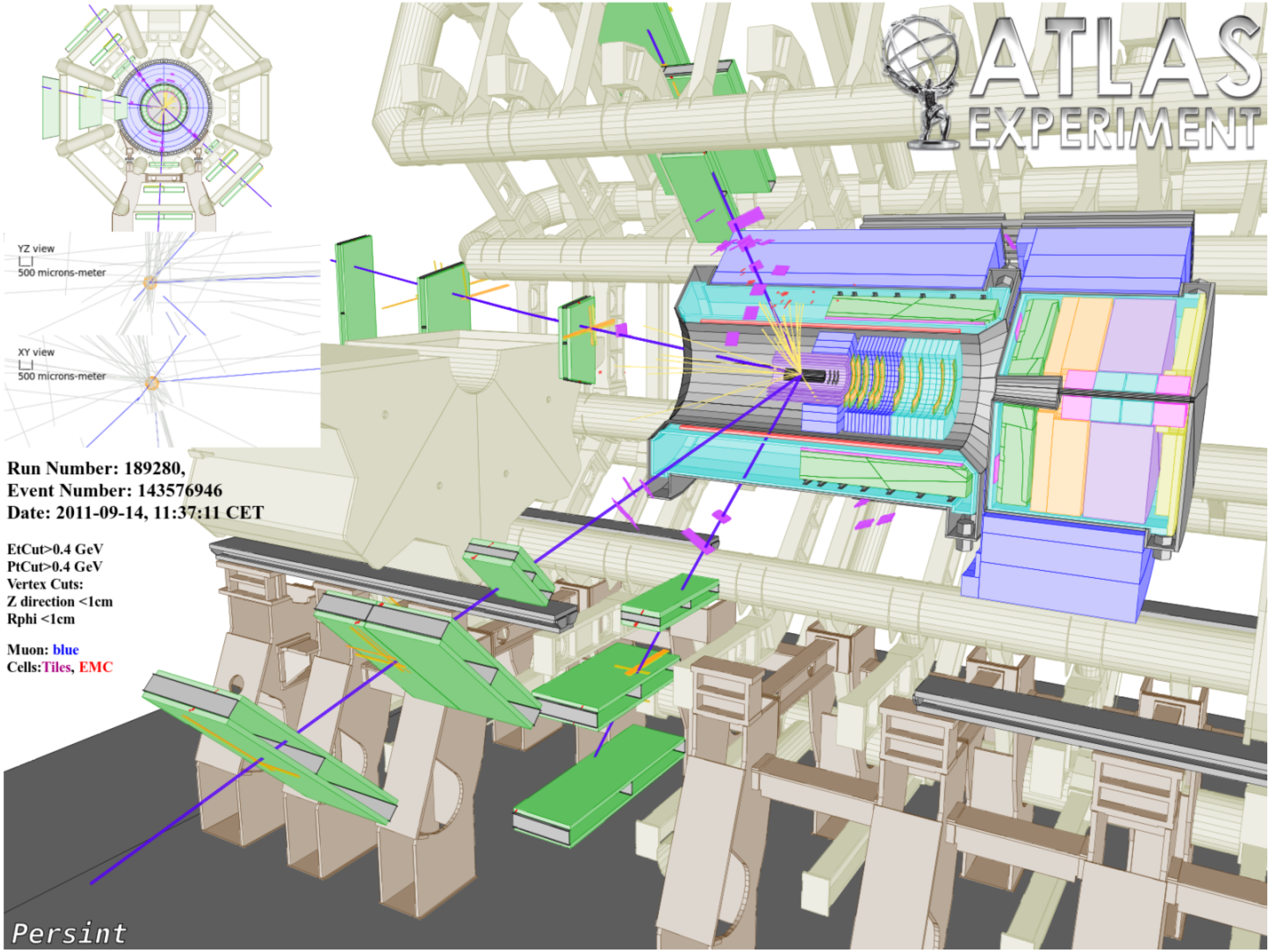
(LEADING ORDER)



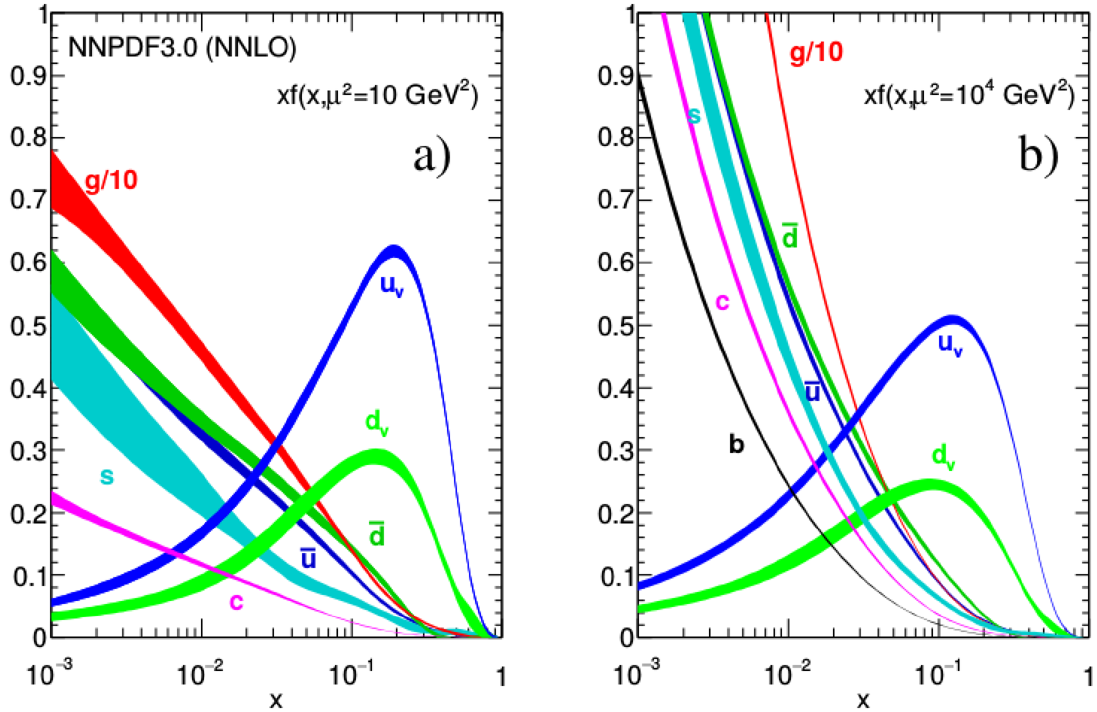
- HADRONIC C.M. ENERGY: $s = (p_1 + p_2)^2$
- PARTONIC C.M. ENERGY: $\hat{s} = x_1 x_2 s$
- MOMENTUM FRACTIONS $x_{1,\,2} = \sqrt{\frac{\hat{s}}{s}} \exp \pm y$; AT LEADING ORDER $\hat{s} = M^2$

PHYSICS AT THE LHC

a Higgs boson is produced in a pp collision, decays into two $\mu^+\mu-$ pairs



THE PDFs

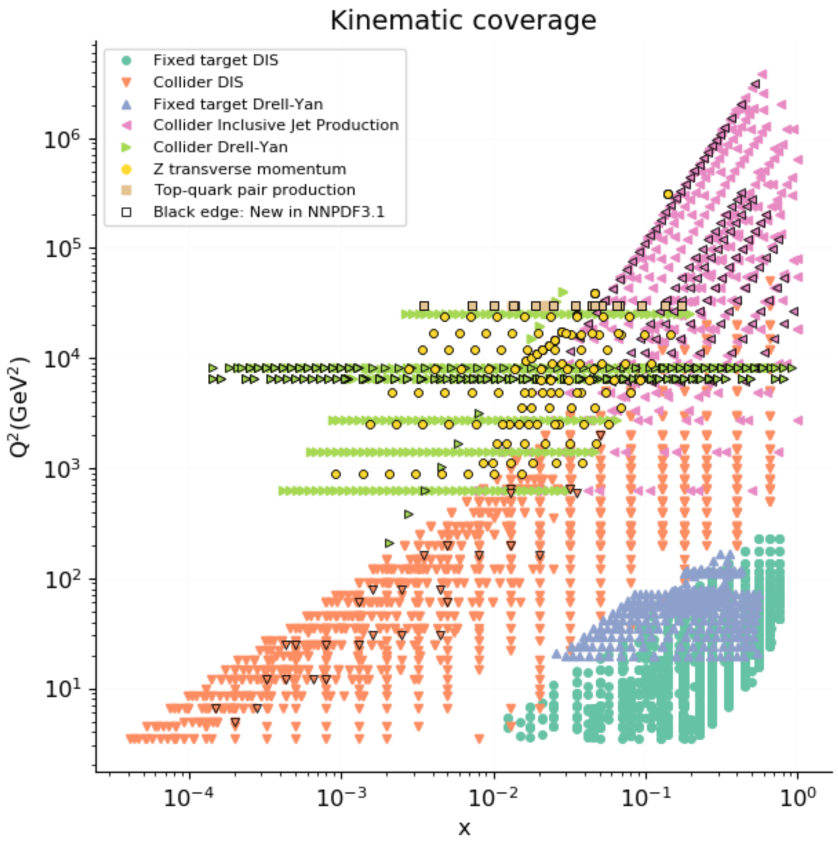


(PDG 2016)

- THE MOMENTUM PROBABILITY DENSITY $xf_i(x)$ IS SHOWN AT TWO DIFFERENT SCALES (RESOLUTIONS) (LEFT $\Rightarrow$ LOW SCALE; RIGHT $\Rightarrow$ HIGH SCALE)
- PDFs VS x AT ONE SCALE $Q_0^2 \Rightarrow$ DETERMINED FOR ALL SCALES BY EVOLUTION EQUATIONS
- AS $x \geq 1$ KINEMATIC CONSTRAINT $f_i(x) = 0$
- "VALENCE" UP AND DOWN: PEAKED AT $x \sim 0.3$; EXPECT $f_x(x) \underset{x\to 1}{\sim} (1-x)_i^\beta$
- "SEA" ANTIQUARK AND GLUON GROW AT SMALL x

PDF DETERMINATION

DATA $\to$ PARTON DISTRIBUTIONS

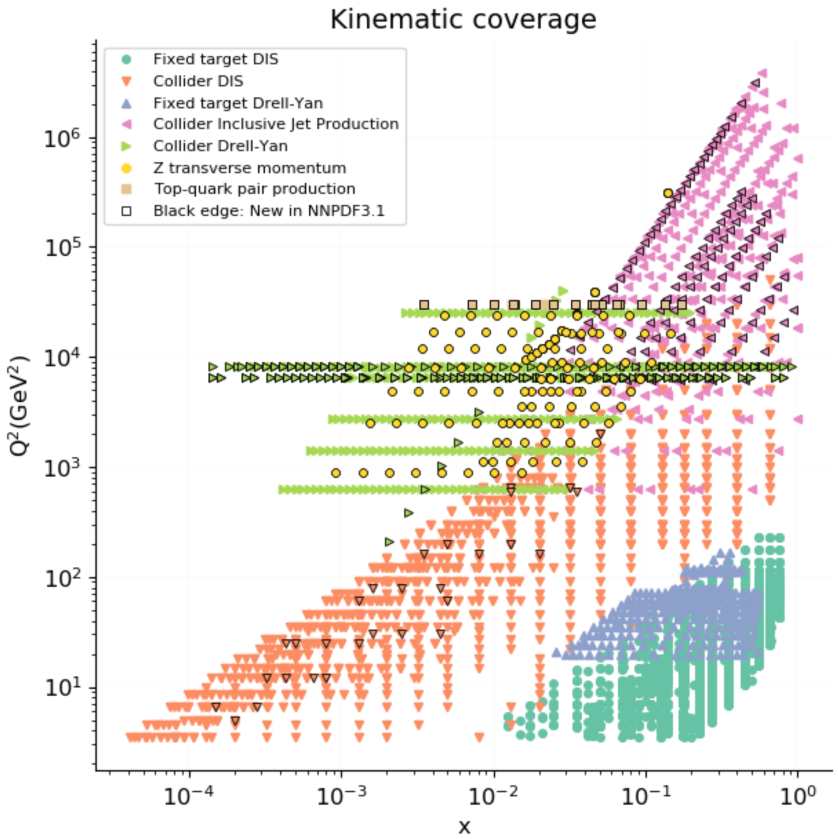


HOW?

- FROM PHYSICAL OBSERVABLES TO PDFS: SOLVE EVOLUTION EQUATIONS, CONVOLUTE WITH PARTONIC CROSS-SECTIONS
- SEPARATE DIFFERENT PDFS: CHOOSE PROCESSES WHICH MEASURE DIFFERENT COMBINATIONS (UP, DOWN...)
- FIT?

PDF DETERMINATION

DATA $\rightarrow$ PARTON DISTRIBUTIONS



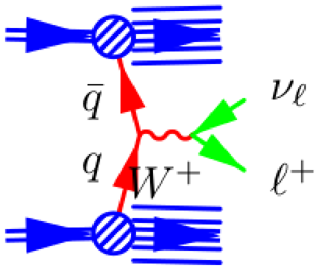
ISSUES AND TASKS:

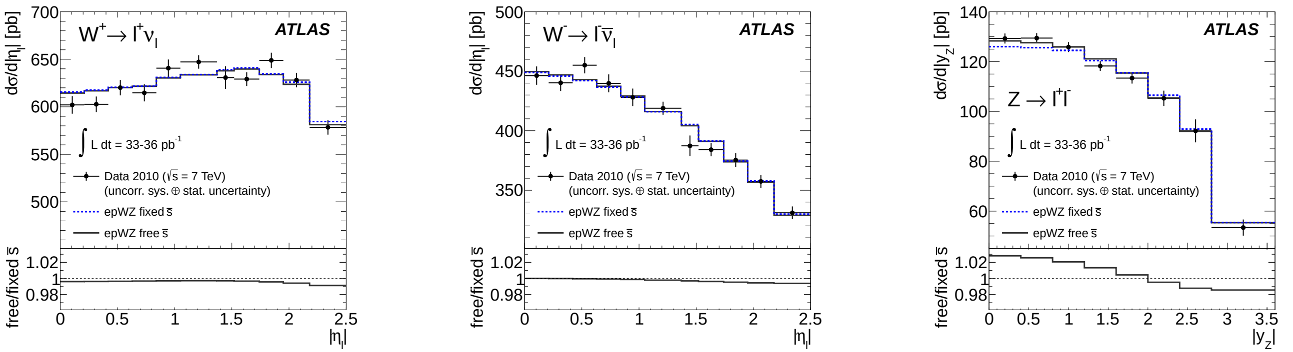
- FROM PHYSICAL OBSERVABLES TO PDFS: SOLVE EVOLUTION EQUATIONS, CONVOLUTE WITH PARTON-LEVEL CROSS-SECTIONS
- DISENTANGLING PDFS: CHOOSE A BASIS OF PDFS ($2N_f$ QUARKS + 1 GLUON) & A SET OF SUITABLE PHYSICAL PROCESSES TO DETERMINE THEM ALL
- PROBABILITY IN THE SPACE OF FUNCTIONS: CHOOSE A STATISTICAL APPROACH (HESSIAN, MONTE CARLO, . . .)
- UNCERTAINTY ON FUNCTIONS: CHOOSE A FUNCTIONAL FORM

DISENTANGLING PDFs

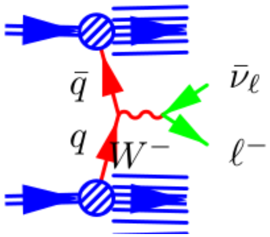
EXAMPLE: $W^{\pm}$ AND Z PRODUCTION

W AND Z CROSS SECTIONS



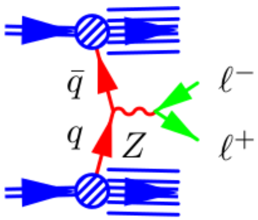


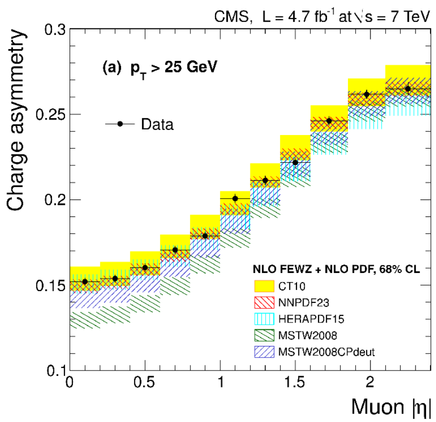
ATLAS (2012)



$$\sigma^{p\bar{p}}_{W^+} = u\bar{d} + c\bar{s}; \quad \sigma^{p\bar{p}}_{Z} = u\bar{u} + d\bar{d} + s\bar{s}:$$ STRANGENESS DETERMINED BY COMPARISON

W MUON ASYMMETRY





CMS (2013)

$$\frac{\sigma^{p\bar{p}}_{W^+}}{\sigma^{p\bar{p}}_{W^-}} = \frac{u(x_1)\bar{d}(x_2)+\bar{d}(x_1)u(x_2)}{d(x_1)\bar{u}(x_2)+\bar{u}(x_1)d(x_2)}$$

"VALENCE" $x \Rightarrow$ NEGLECT STRANGENESS

$\Rightarrow$ DETERMINE $\bar{u} - \bar{d}$

DETERMINING PDFS
MODEL-DEPENDENT APPROACH

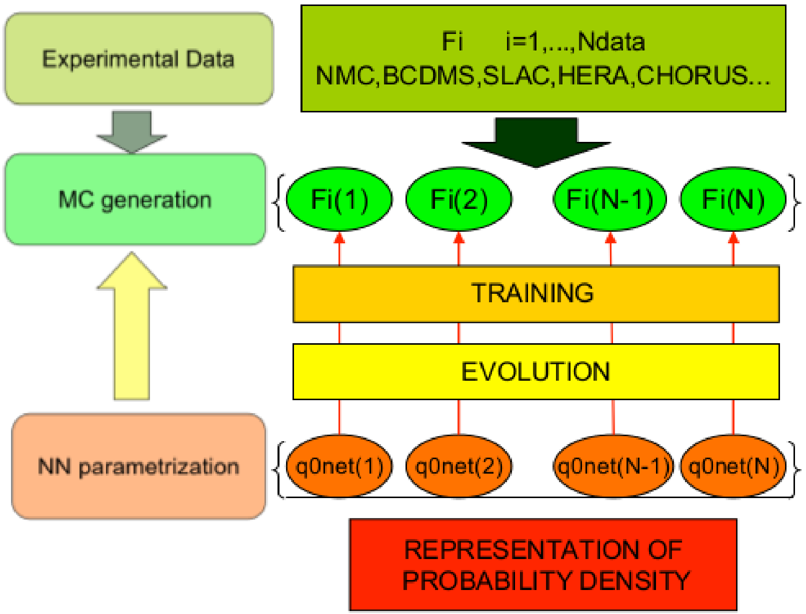
- CHOOSE A FIXED FUNCTIONAL FORM
  - SINCE 1973, PHYSICALLY MOTIVATED ANSATZ $f_i(x, Q_0^2) = x^{\alpha}(1-x)^{\beta} g_i(x)$; $g_i(x)$ POLYNOMIAL IN x OR $\sqrt{x}$
  - MMHT 2015:
    * BASIS FUNCTIONS g; $u_v = u - \bar{u}$; $d_v = d - \bar{d}$; $S = 2(\bar{u} + \bar{d}) + s + \bar{s}$; $s_+ = s + \bar{s}$; $\Delta = \bar{d} - \bar{u}$; $s_- = s - \bar{s}$.
    * FOR ALL BUT Δ s_-, $g \Rightarrow x f_i(x, Q_0^2) = A x^{\alpha}(1-x)^{\beta}\left(1 + \sum_{i=1}^{4} a_i T_i(y(x))\right)$; 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 $x g(x, Q_0^2) = A x^{\alpha}(1-x)^{\beta}\left(1 + \sum_{i=1}^{2} a_i T_i(y(x))\right) + A' x T \alpha'(1-x)^{\beta'}$
    * SEA ASYMMETRY $x\Delta(x, Q_0^2) = A x^{\alpha}(1-x)^{\beta}(1 + \gamma x + \epsilon x^2)$
    * STRANGENESS ASYMMETRY $x\Delta(x, Q_0^2) = A x^{\alpha}(1-x)^{\beta}(1 - x/x_0)$
    * 41 PARAMETERS, 4 FIXED BY SUM RULES
    * 12 PARMS FIXED AT BEST FIT, REMAINING 25 USED FOR (HESSIAN) COVARIANCE MATRIX
- WHAT ABOUT MODEL DEPENDENCE?

THE NNPDF APPROACH

BASIC IDEA: MONTE CARLO SAMPLING OF THE PROBABILITY MEASURE IN THE (FUNCTION) SPACE OF PDFs

- GENERATE A SET OF MONTE CARLO REPLICAS $\sigma^{(k)}$ OF THE ORIGINAL DATASET $\sigma^{(\mathrm{data})}$
  $\Rightarrow$ REPRESENTATION OF $\mathcal{P}[\sigma]$ AT DISCRETE SET OF POINTS IN DATA SPACE
- FIT A PDF REPLICA TO A DATA REPLICA
  $\Rightarrow$ EACH PDF REPLICA $f_i^{(k)}$ IS A BEST-FIT PDF SET FOR GIVEN DATA REPLICA
- THE SET OF NEURAL NETS IS A REPRESENTATION OF THE PROBABILITY DENSITY:

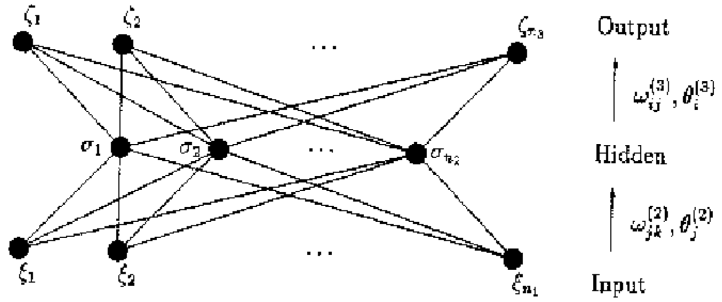
$$\langle f_i \rangle = \frac{1}{N_{rep}} \sum_{k=1}^{N_{rep}} f_i^{(k)}$$

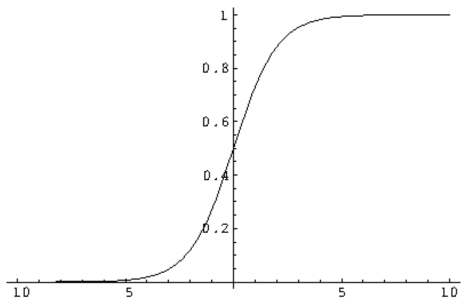


NEURAL NETWORKS

- EACH PDF REPLICA FITTED TO A DATA REPLICA
  $\Rightarrow$ NEED BEST-FIT, COVARIANCE MATRIX IN PARAMETER SPACE NOT NEEDED
- CAN USE VERY LARGE PARAMETRIZATION

NEURAL NETWORKS





MULTILAYER FEED-FORWARD NETWORKS

- Each neuron receives input from neurons in preceding layer and feeds output to neurons in subsequent layer
- Activation determined by weights and thresholds
  $\xi_i = g\left(\sum_j \omega_{ij}\xi_j - \theta_i\right)$
- Sigmoid activation function
  $g(x) = \frac{1}{1+e^{-\beta x}}$

EXAMPLE: A 1-2-1 NN

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

THANKS TO NONLINEAR BEHAVIOUR, ANY FUNCTION CAN BE REPRESENTED BY A SUFFICIENTLY BIG NEURAL NETWORK

GENETIC MINIMIZATION
BASIC IDEA: RANDOM MUTATION OF THE NN PARAMETER, SELECTION OF THE FITTEST

- LARGE NUMBER OF MUTANT (~ 100) PDF SETS GENERATED FROM PARENT
- χ^2 COMPUTED
- BEST-FIT KEPT & PASSED TO NEXT GENERATION

$$w \to w + \frac{\eta r_\delta}{N_{\rm ite}^{r_{\rm ite}}}$$

CHOICES

- MUTATION RATE η
- POINTLIKE VS. NODAL MUTATION
- NUMBER (POINTLIKE) OR PROBABILITY (NODAL) OF MUTATIONS
- TARGETED WT: WEIGTHS $p_i = E_i/E_i^{\rm targ}$
- GA EPOCHS: $N_{\rm gen}^{\rm mut}$

	$N_{\rm gen}^{\rm wt}$	$N_{\rm gen}^{\rm mut}$	$N_{\rm gen}^{\rm max}$	$E^{\rm sw}$	$N_{\rm mut}^{a}$	$N_{\rm mut}^{b}$
NNPDF 2.3	10000	2500	50000	2.3	80	30
NNPDF 3.0	–	-	30000	-	80	-

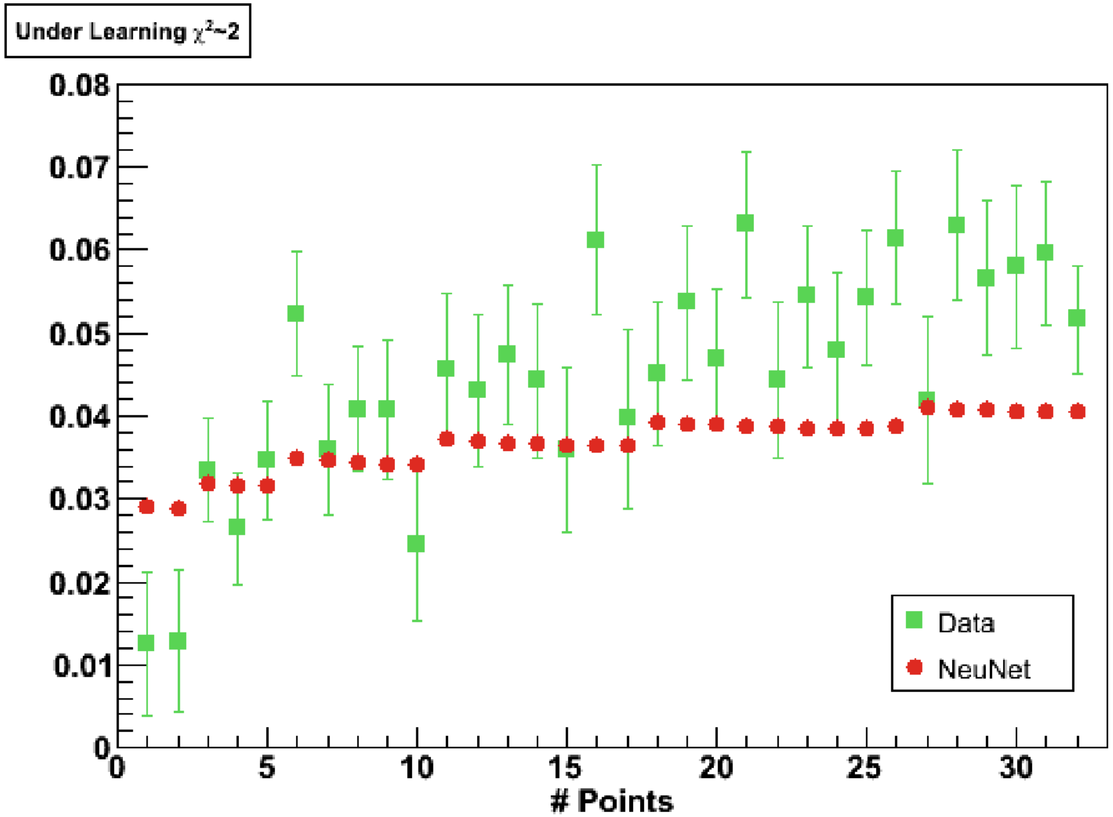
NNPDF2.3		
Single Parameter Mutation		
PDF	$N_{\rm mut}$	η
$\Sigma(x)$	2	10, 1
$g(x)$	3	10, 3, 0.4
$T_3(x)$	2	1, 0.1
$V(x)$	3	8, 1, 0.1
$\Delta_S(x)$	3	5, 1, 0.1
$s^+(x)$	2	5, 0.5
$s^-(x)$	2	1, 0.1

NNPDF3.0		
Nodal Mutation		
PDF	$P_{\rm mut}$	η
$\Sigma(x)$	5% per node	15
$g(x)$	5% per node	15
$V(x)$	5% per node	15
$V_3(x)$	5% per node	15
$V_8(x)$	5% per node	15
$T_3(x)$	5% per node	15
$T_8(x)$	5% per node	15

NEURAL LEARNING

- ONE CAN CHOOSE A HIGHLY REDUNDANT PARAMETRIZATION
  EXAMPLE: NNPDF: $2-5-3-1$ NN FOR EACH PDF: $37 \times 7 = 259$ PARAMETERS
- COMPLEXITY INCREASES AS THE FITTING PROCEEDS
- $\Rightarrow$ THE BEST FIT IS NOT THE ABSOLUTE MINIMUM:
  MUST LOOK FOR OPTIMAL LEARNING POINT

UNDERLEARNING



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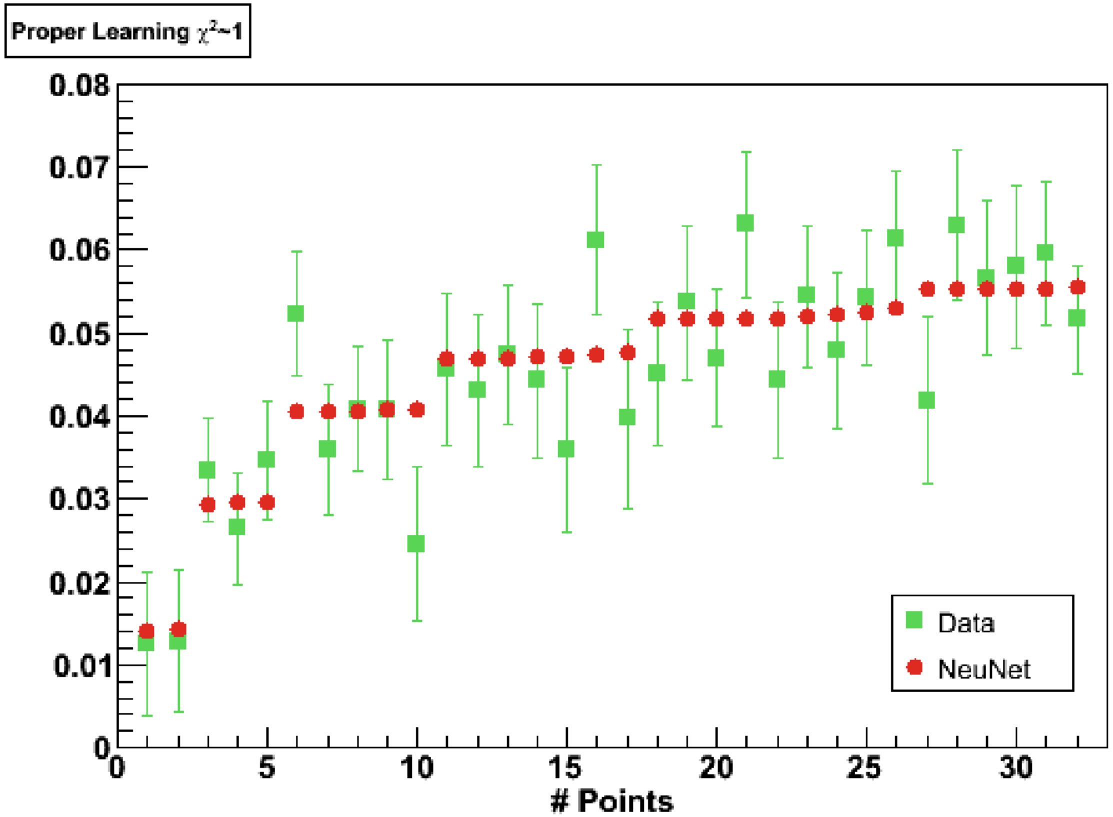
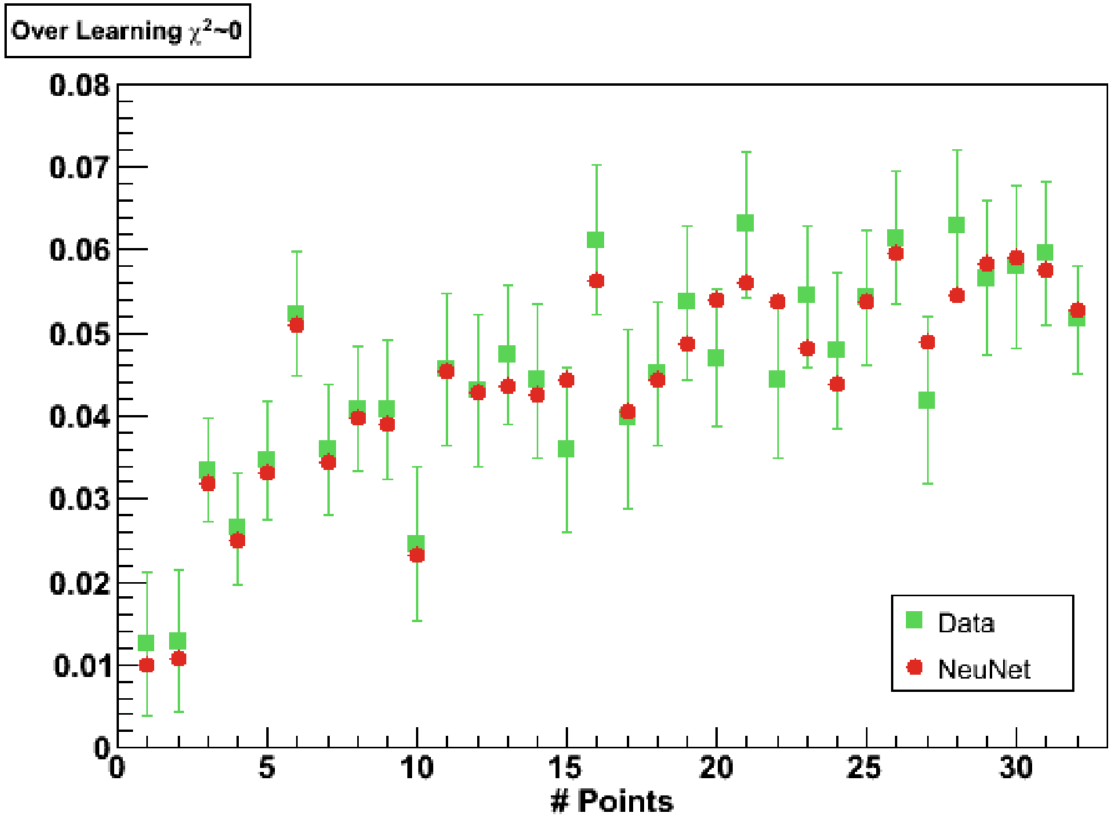
PROPER LEARNING



NEURAL LEARNING

- ONE CAN CHOOSE A HIGHLY REDUNDANT PARAMETRIZATION
  EXAMPLE: NNPDF: $2-5-3-1$ NN FOR EACH PDF: $37 \times 7 = 259$ PARAMETERS
- COMPLEXITY INCREASES AS THE FITTING PROCEEDS
- $\Rightarrow$ THE BEST FIT IS NOT THE ABSOLUTE MINIMUM:
  MUST LOOK FOR OPTIMAL LEARNING POINT

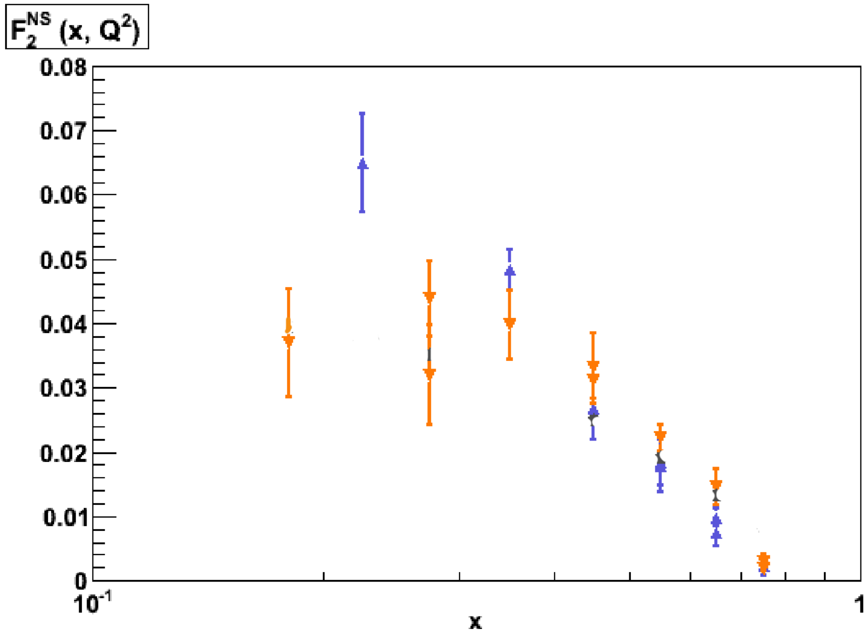
OVERLEARNING



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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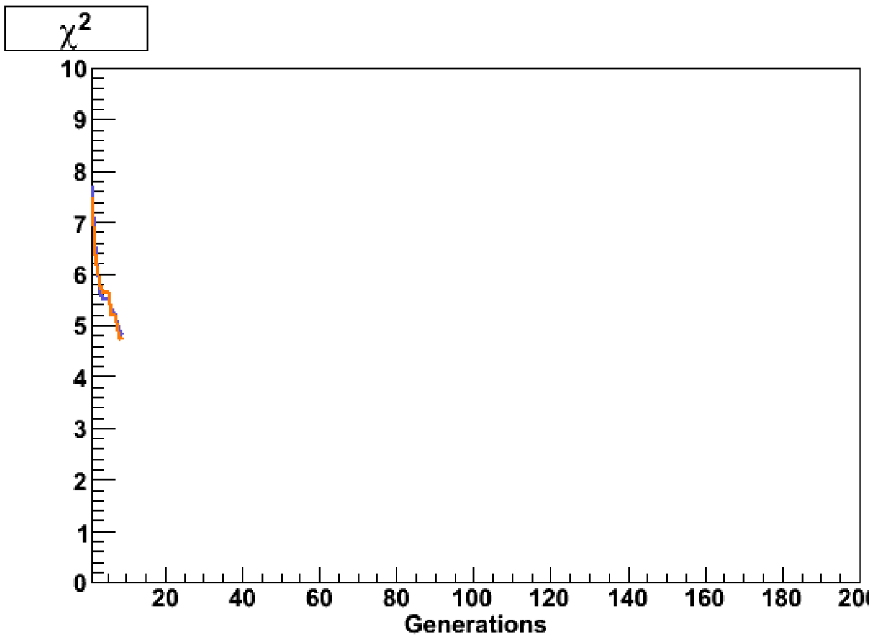
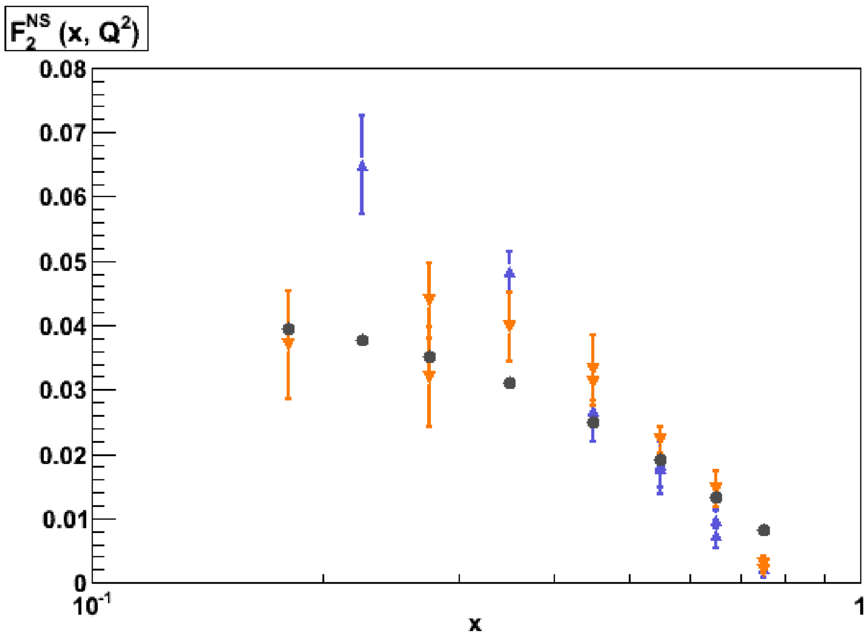
GO!





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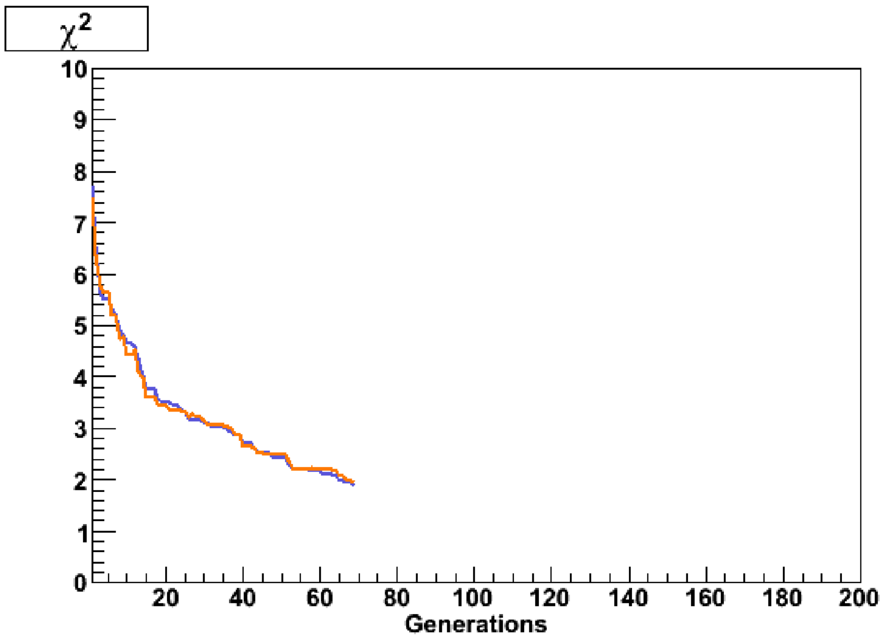
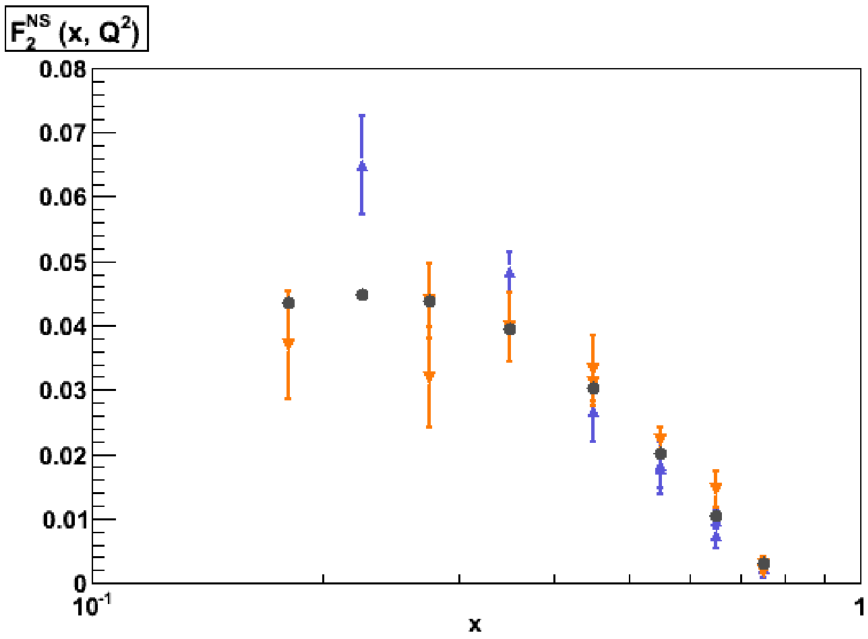
STOP!





OPTIMAL FIT: CROSS-VALIDATION

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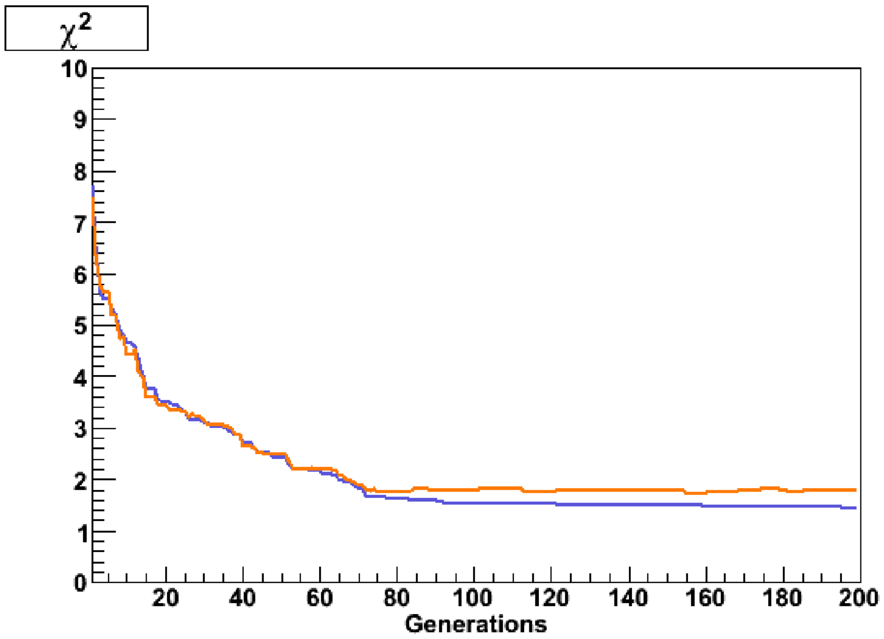
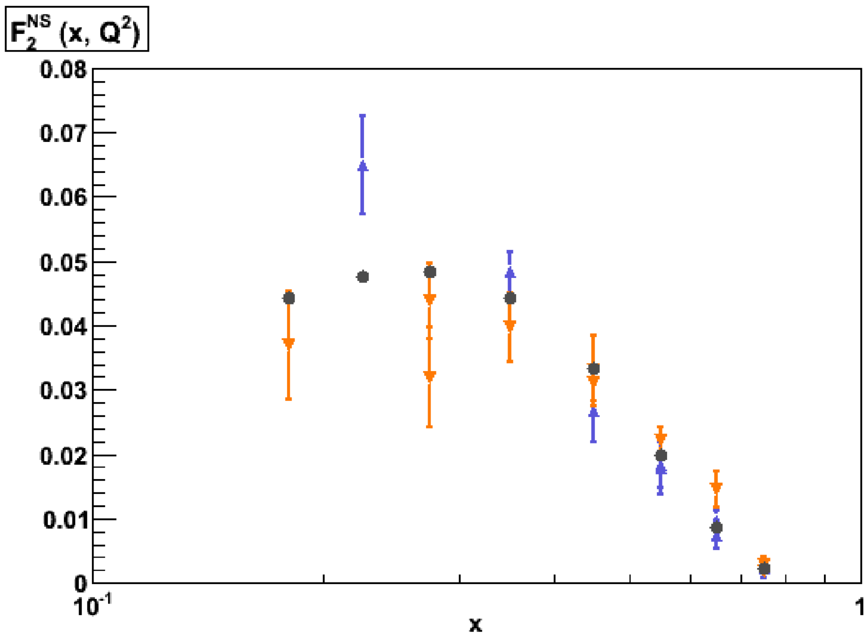
- WHEN THE VALIDATION χ^2 STOPS DECREASING, STOP THE FIT

TOO LATE!





TESTING THE PDF DETERMINATION:

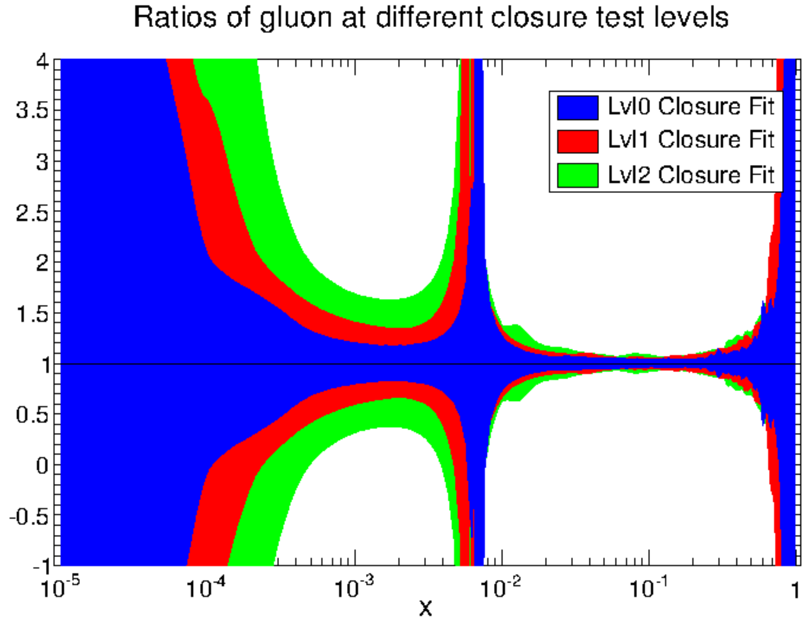
CLOSURE TESTS

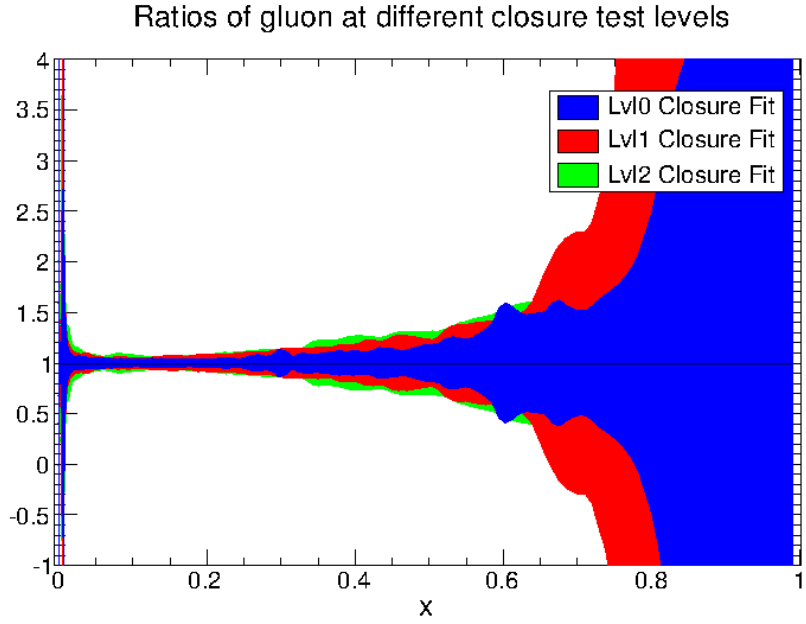
- ASSUME PDFS KNOWN: GENERATE FAKE EXPERIMENTAL DATA
- CAN DECIDE DATA UNCERTAINTY (ZERO, OR AS IN REAL DATA, OR . . .)
- FIT PDFS TO FAKE DATA
- CHECK WHETHER FIT REPRODUCES UNDERLYING "TRUTH":
  - CHECK WHETHER TRUE VALUE GAUSSIANLY DISTRIBUTED ABOUT FIT
  - CHECK WHETHER UNCERTAINTIES FAITHFUL
  - TRACE DIFFERENT SOURCES OF UNCERTAINTY

TRACING SOURCES OF UNCERTAINTY

- LEVEL 0: FAKE DATA GENERATED WITH NO UNCERTAINTY
  $\rightarrow$ INTERPOLATION AND EXTRAPOLATION UNCERTAINTY
- LEVEL 1-2: FAKE DATA GENERATED WITH SAME UNCERTAINTY AS REAL DATA (INCLUDING CORRELATIONS)
- LEVEL 1: NO PSEUDODATA REPLICAS:
  $\Rightarrow$ REPLICAS FITTED TO SAME DATA OVER AND OVER AGAIN
  $\rightarrow$ FUNCTIONAL UNCERTAINTY DUE TO INFINITY OF EQUIVALENT MINIMA
- LEVEL 2: STANDARD NNPDF METHODOLOGY
  $\Rightarrow$ REPLICAS FITTED TO PSEUDODATA REPLICAS
  $\rightarrow$ DATA UNCERTAINTY
- THREE SOURCES OF UNCERTAINTY COMPARABLE IN DATA REGION

THE GLUON: LEVEL 0, LEVEL 1 AND LEVEL 2



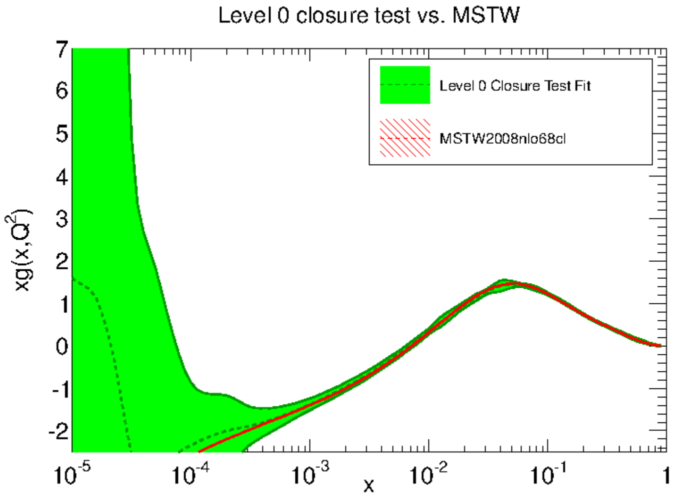


FITTING EFFICIENCY

LEVEL 0

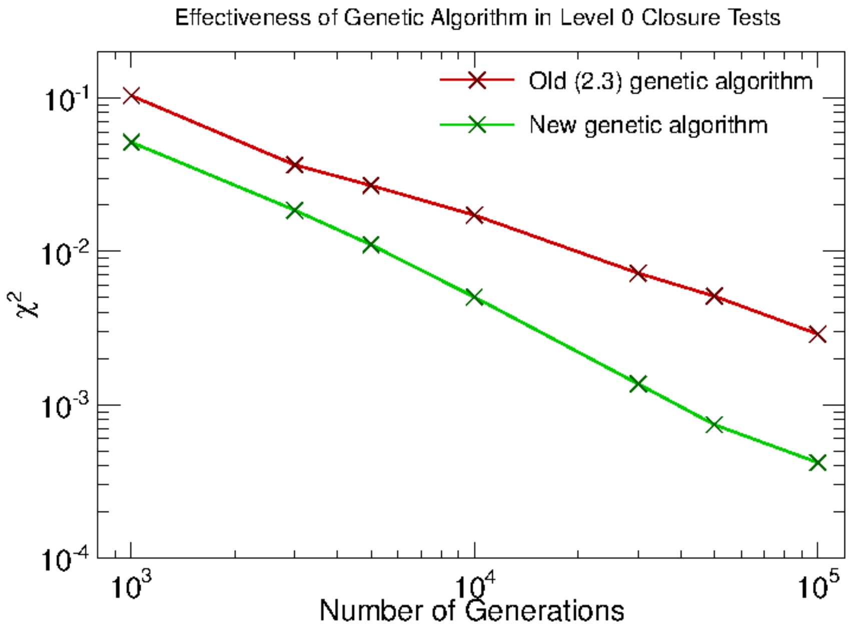
- ASSUME VANISHING EXPERIMENTAL UNCERTAINTY
- MUST BE ABLE TO GET $\chi^2 = 0$
- UNCERTAINTY AT DATA POINTS TENDS TO ZERO (NOT NECESSARILY ON PDF!)
  DEFINE $\phi \equiv \sqrt{\langle \chi^2_{rep}\rangle - \chi^2}$, EQUALS FIT UNCERTAINTY/DATA UNCERTAINTY; CHECK $\phi \to 0$
- CAN STUDY EFFICIENCY OF MINIMIZATION

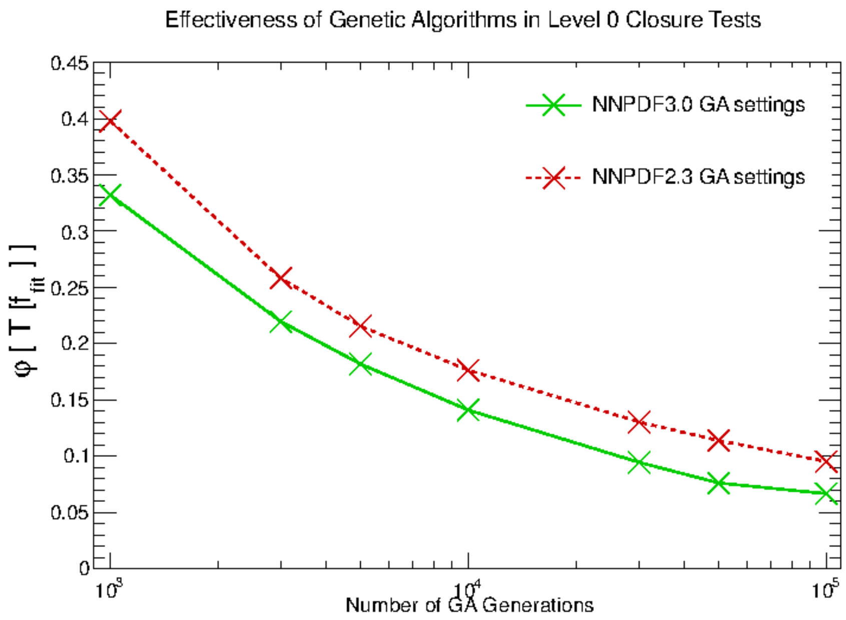
THE GLUON



FRACTIONAL UNCERTAINTY VS TRAINING LENGTH

χ^2 VS TRAINING LENGTH

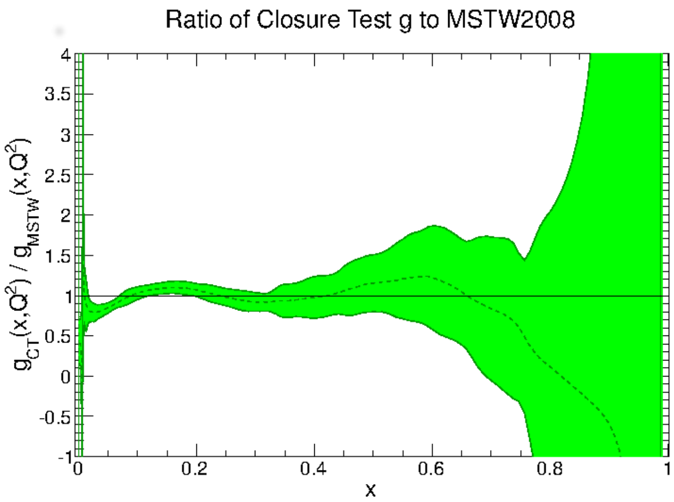




TESTING THE PDF DETERMINATION

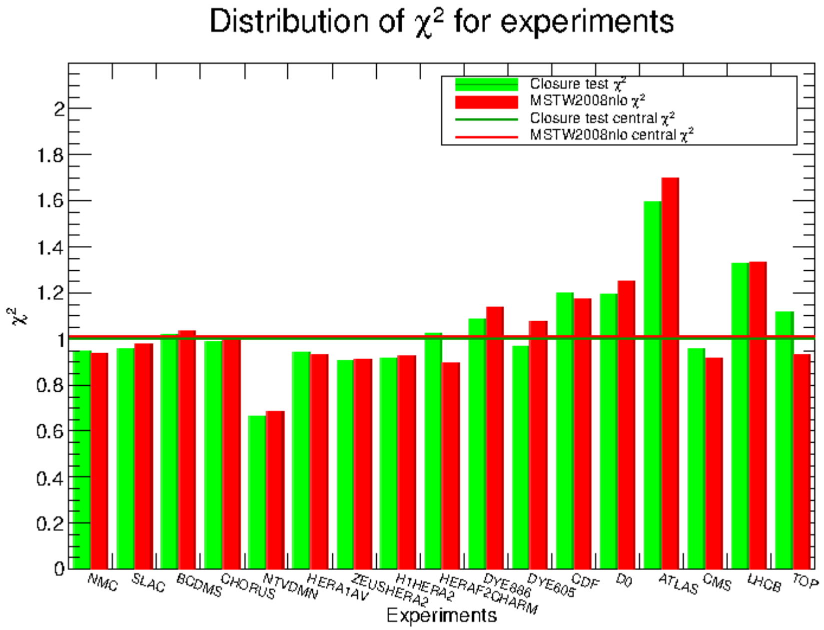
RESULTS

THE GLUON: FITTED/"TRUE"

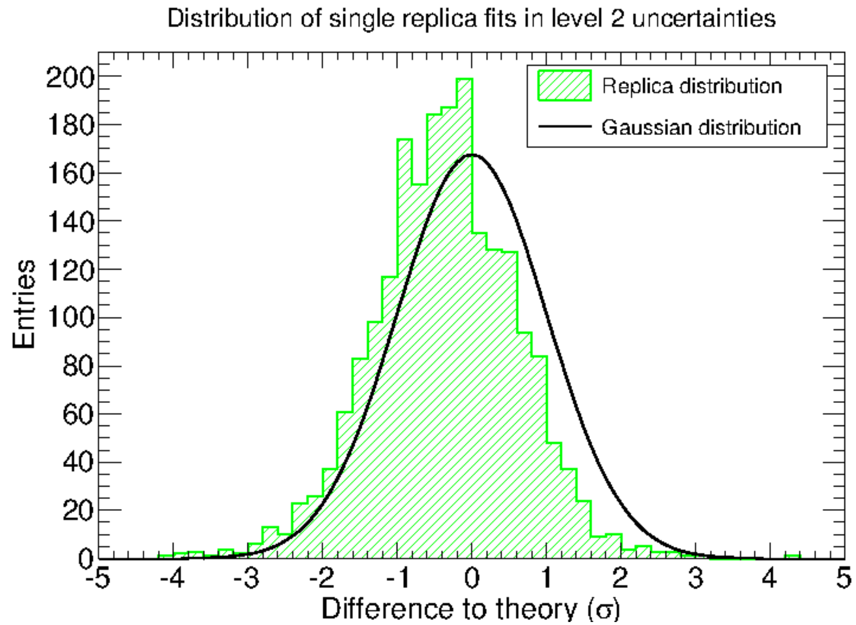


- CENTRAL VALUES: COMPARE FITTED VS. "TRUE" χ^2 BOTH FOR INDIVIDUAL EXPERIMENTS & TOTAL DATASET FOR TOTAL $\Delta\chi^2 = 0.001 \pm 0.003$
- UNCERTAINTIES: DISTRIBUTION OF DEVIATIONS BETWEEN FITTED AND "TRUE" PDFs SAMPLED AT 20 POINTS BETWEEN 10^{-5} AND 1 FIND 0.699% FOR ONE-SIGMA, 0.948% FOR TWO-SIGMA C.L.

LEVEL-2 FITTED χ^2 VS "TRUE"

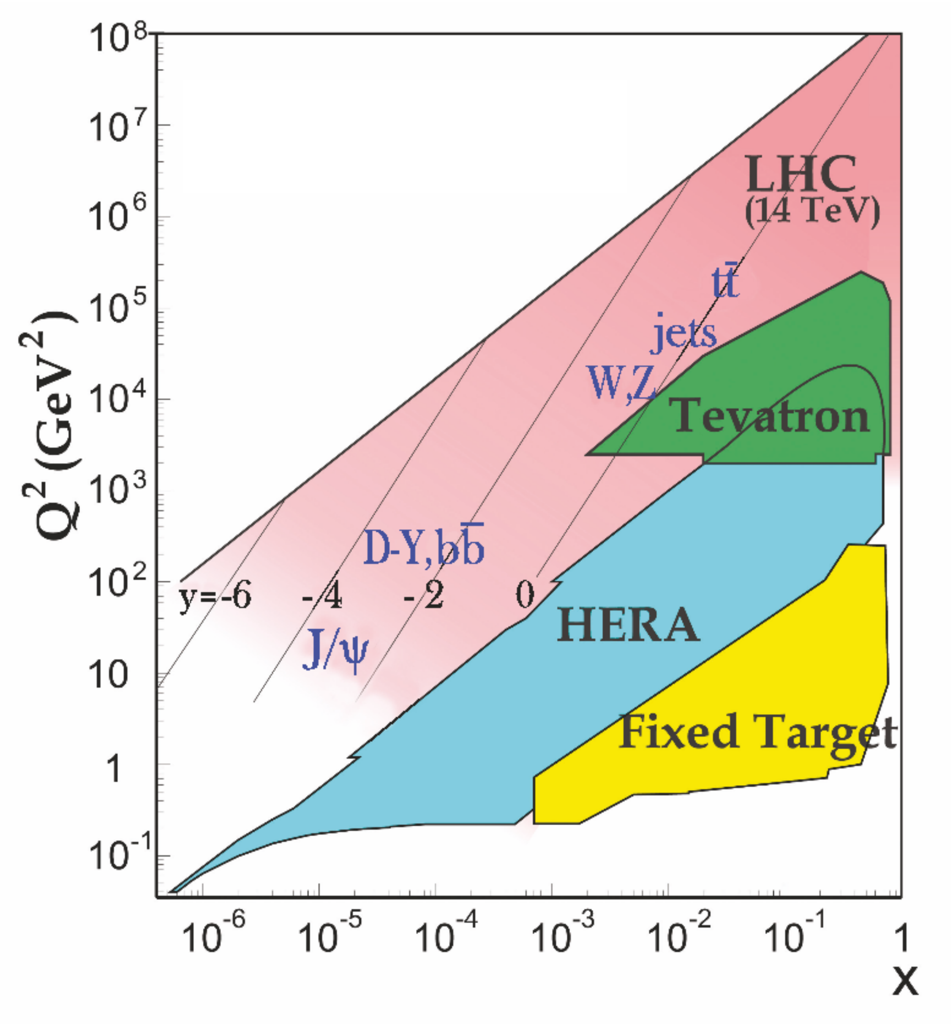


NORM. DISTRIBUTION OF DEVIATIONS

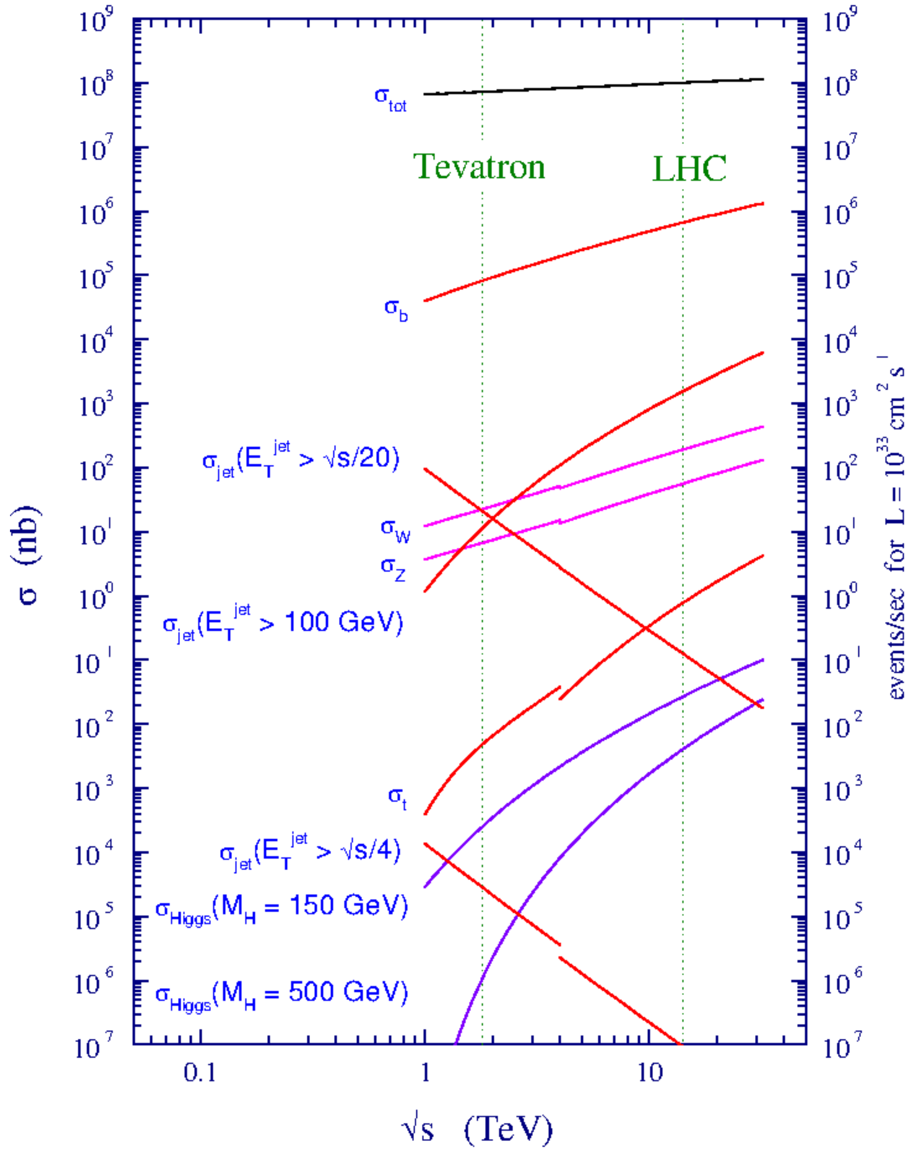


BEFORE AND AFTER THE LHC I

KINEMATIC PLANE



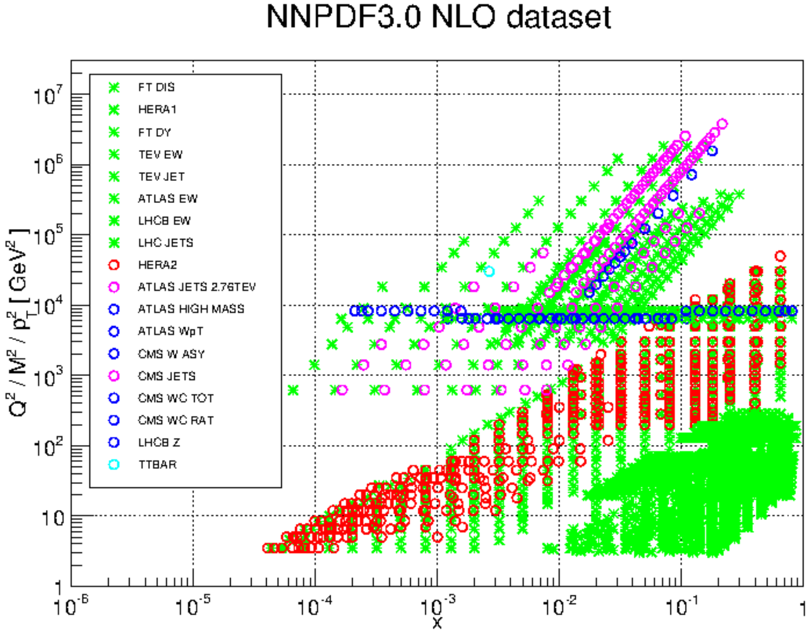
HADRONIC CROSS-SECTIONS



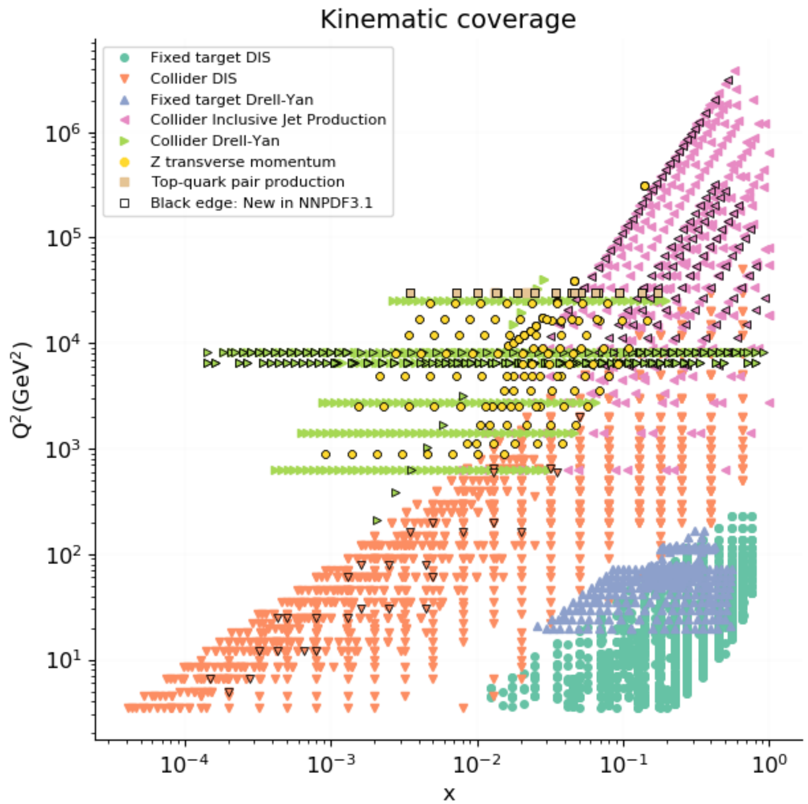
- Q^2 : INVARIANT MASS OF FINAL STATE $\Rightarrow$ WIDENING OF AVAILABLE PROCESSES
- AS ENERGY GROWS, DROP OF CROSS-SECTION MAY BE OFFSET BY GROWTH OF SMALL x PDFs

BEFORE AND AFTER THE LHC II
PDFs WITH RUN I DATA

NNPDF3.0 (2014) DATASET



NNPDF3.1 (2017) DATASET

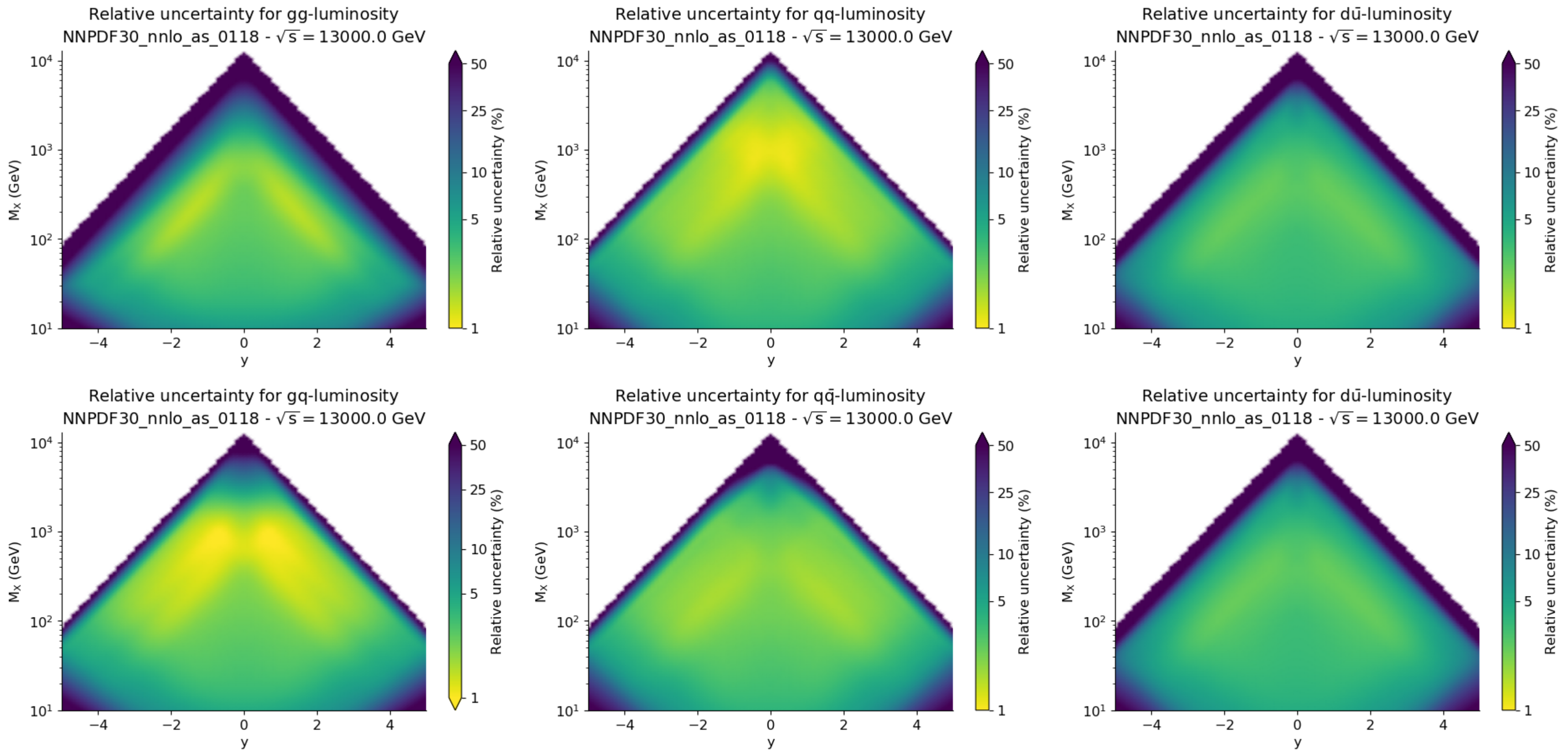


NEW DATA (NNPDF3.1 VS NNPDF3.0):

- TEVATRON LEGACY Z RAPIDITY, W ASYMMETRY & JET DATA
- ATLAS W, Z RAPIDITY, AND TOTAL XSECT (INCL. 13TEV), HIGH AND LOW MASS DY, JETS
- CMS W ASYMMETRY, $W + c$ TOTAL & RATIO, DOUBLE-DIFFERENTIAL DY AND JETS
- LHCB W AND Z RAPIDITY DISTRIBUTIONS
- ATLAS AND CMS Z p_T DISTRIBUTIONS
- ATLAS AND CMS TOP TOTAL CROSS-SECTION & DIFFERENTIAL RAPIDITY DISTRIBUTION

THE IMPACT OF LHC DATA
PDF UNCERTAINTIES: PAST $\Rightarrow$ PRESENT (NNPDF3.0 NNLO)

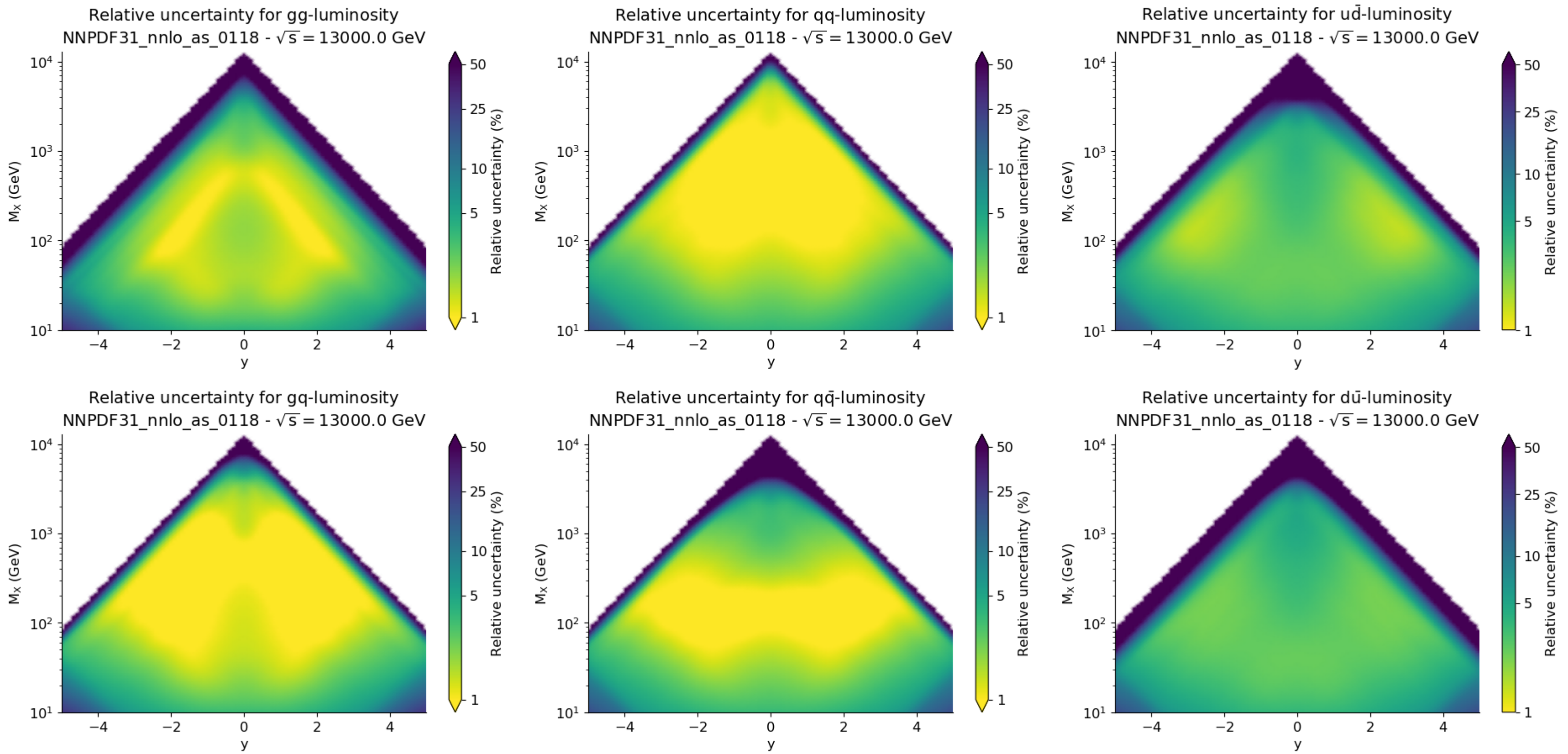
GLUON SINGLET FLAVORS



- GLUON BETTER KNOWN AT SMALL x, VALENCE QUARKS AT LARGE x, SEA QUARKS IN BETWEEN
- SWEET SPOT: VALENCE Q - G; UNCERTAINTIES DOWN TO 1%
- UP BETTER KNOWN THAN DOWN; FLAVOR SINGLET BETTER THAN INDIVIDUAL FLAVORS

THE IMPACT OF LHC DATA
PDF UNCERTAINTIES: PRESENT ⇒ FUTURE (NNPDF3.1 NNLO)

GLUON SINGLET FLAVORS

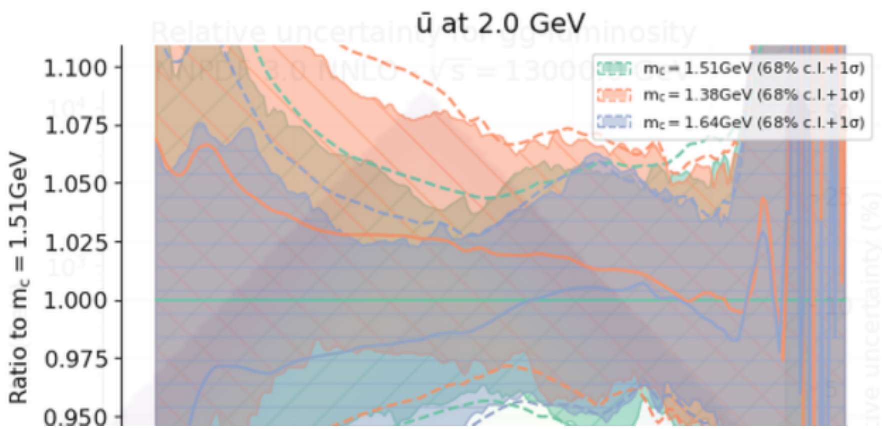


- GLUON BETTER KNOWN AT SMALL x, VALENCE QUARKS AT LARGE x, SEA QUARKS IN BETWEEN
- SWEET SPOT: VALENCE Q - G; UNCERTAINTIES DOWN TO 1%
- UP BETTER KNOWN THAN DOWN; FLAVOR SINGLET BETTER THAN INDIVIDUAL FLAVORS
- NEW LHC DATA ⇒ SIZABLE REDUCTION IN UNCERTAINTIES

$\mathrm{N^3PDF}$

N3PDF
Machine Learning • PDFs • QCD

The **N3PDF** project, led by PI **Stefano Forte**, aims at revolutionizing the theory of strong interactions and its application to the determination of the structure of the proton, by introducing extensively techniques of artificial intelligence (AI). The core of the project is the development of an AI agent for the determinations of the parton distributions which encode the quark and gluon structure of the proton, using machine learning techniques. The project also includes an integrated set of studies on higher-order computations and resummation in perturbative QCD, and the development of parton distributions interfaced to resummation and Monte Carlo generators. The project will work in synergy with the NNPDF collaboration, to which it will provide methods and tools, and from which it will gain physics input and insight.



Tweets by @NNPDF_Team

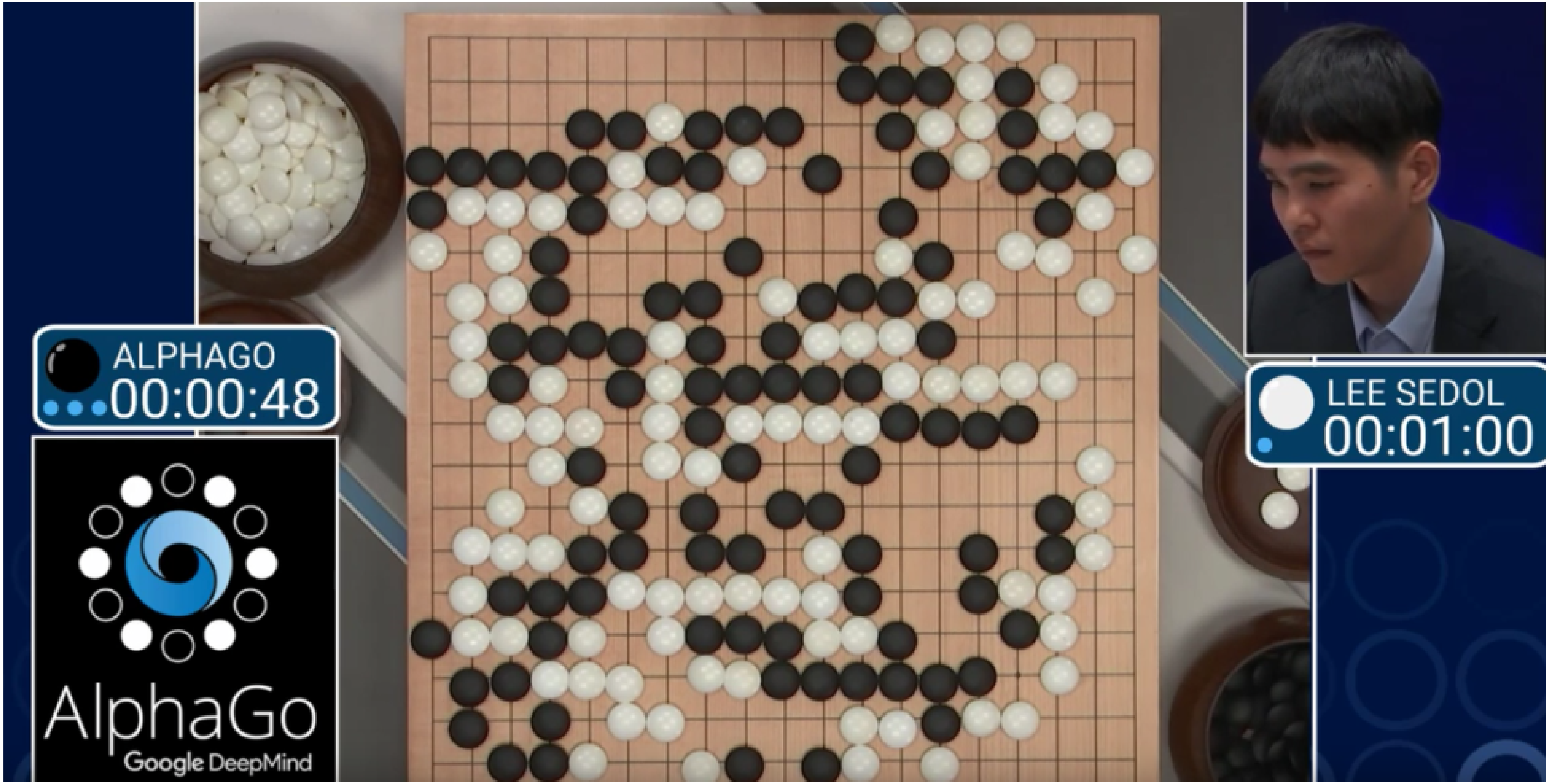
NNPDF_Team Retweeted
Jon Butterworth
@jonmbutterworth
After 40 years of studying the strong nuclear force, a revelation theguardian.com/science/life-a...
Me at Life & #Physics on BFKL and all that.

Embed View on Twitter

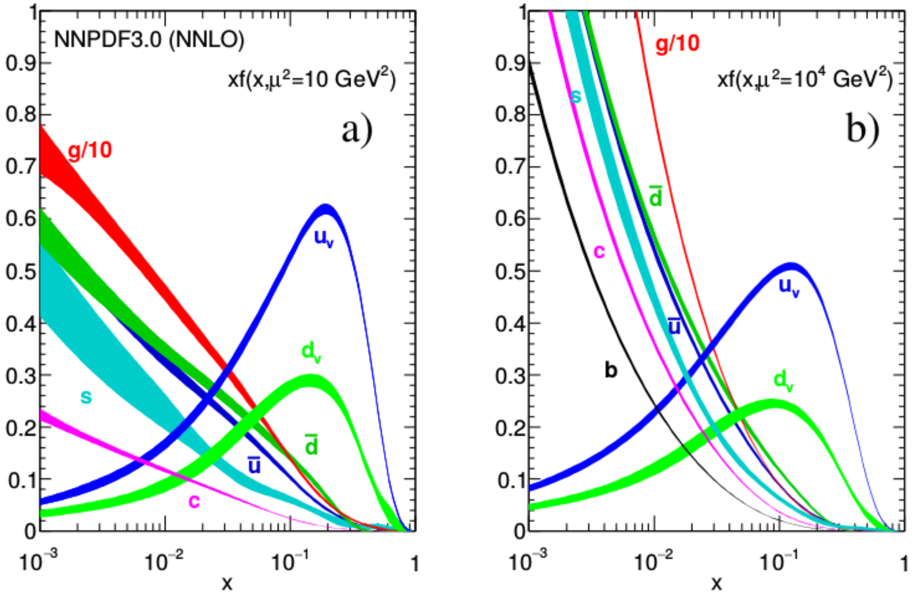
JOBS

There are currently no positions available but we will be looking for two PhD students very soon!

AI & GO



AI & PDFs



N3PDF

Machine Learning • PDFs • QCD