

On determinations of the strong coupling constant from hadronic data

High Energy Physics Seminar, Cavendish Laboratory

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European Research Council

NNPDF

Introduction: Theoretical uncertainties at the LHC

The main uncertainties in a theoretical calculation of a process at the LHC:

- Missing higher orders uncertainties (MHO).
- Uncertainties on the PDF.
- Uncertainties on α_S .

Example: ggH :

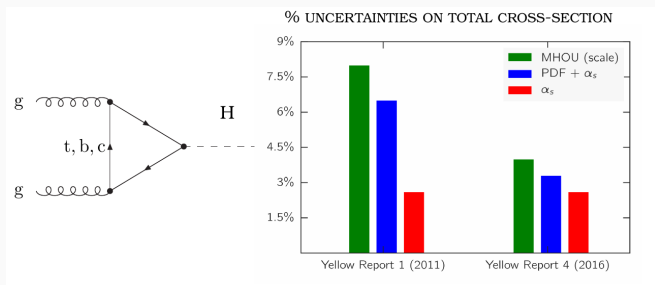


Figure 1: (S.Forte, Lattice 2017)

State of the affairs

- Difficult to provide a statistical interpretation to all three of these uncertainties. Rely on a decision *by committee*.
- Improvements driven by:
 - Better **calculations**: Generally **decrease** uncertainty.
 - More reliable **methodologies**: Can **decrease or increase** uncertainty.
- In general, recent improvements in MHO and PDF, not in α_S .
- Reliable theory (and th uncertainties) crucial for LHC programme.

Estimation of Missing Higher Order Uncertainties

MHOU: Usually estimated through scale variations.

- Normative source: *Yellow Report 4*.
- Central scale setting can make a large difference [e.g jets at NNLO, Currie, et al arXiv:1704.00923].
- Size of the scale variation taken by convention (usually 2 and $\frac{1}{2}$ for μ_r and μ_f).
- Procedure to combine the two scale variations.
 - E.g. $\Delta_{\text{MHOU}} = \left| \frac{[\sigma(2\mu_f, 2\mu_r) - \sigma(\frac{1}{2}\mu_f, \frac{1}{2}\mu_r)]}{2} \right|$ vs max – min of 7-point variation.
 - Uniform vs Gaussian distribution.
- Correlations in multi-process problems: Not well studied.

Improvements driven by calculating higher orders [e.g. ggH at N^3LO , Anastasiou et al, arXiv:1602.00695].

PDFs and PDF uncertainties

- Normative source: PDF4LHC Recommendation [arxiv:1510.03865].
- PDF uncertainties propagate experimental uncertainties to best fit of unbiased interpolants. **MHOU not considered at all!**
- Improvements driven by methodology, new data and theoretical calculations. Leads to agreement between groups.

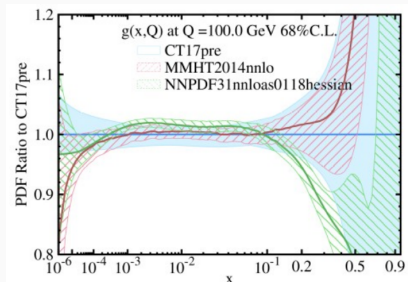


Figure 2: Tie-Jiun Hou, DIS 2018 (Unpublished)

- Normative source: PDG combination [PDG review 2016, Bethke, Dissertori, Salam].
- *World average* on several determinations. Philosophy:

“...be as neutral as possible with regard to disputes in the community about different determinations, with uniform prescriptions applied to all reasonable determinations.”

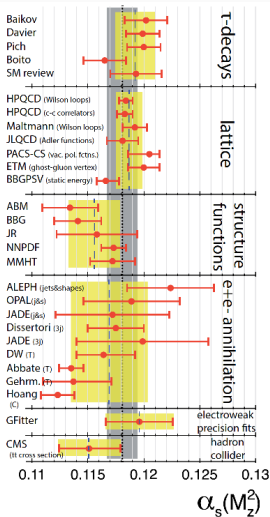
Salam, arxiv:1712.05165

- Current value

$$\alpha_S(M_Z^2) = 0.1181 \pm 0.0013$$

- No updates in 2017 and 2018.

PDG combination



- Only **NNLO** or better determinations considered.
- “Pre averaging”: Take the unweighted mean and the mean error from each process.
- Final number obtained as a weighted “ χ^2 average” over the processes.

Other viewpoints on α_S determination

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 - Updates to **individual determinations**.
 - Identifying **flawed** determinations (potentially bigger effect).

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- PDG world average can be improved by:
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- How reliable is the determination of α_S from PDFs?

- Basic concept: Find best fit in the combined space of (α_S, PDF) of a **large body** of experimental data.
- Compared to Electroweak precision fit [Blas et al, arXiv:1608.01509], the larger dataset implies:
 - More challenging to achieve a good description of all processes (e.g. low scale DIS affected by both MHOU and higher twists).
 - Theoretical problems likely to average out to some extent [Carrazza, Forte, ZK, Rojo, Rottoli, arxiv:1803.07977].
 - More data and more dependence on α_S implies **more precision**.

Challenges extracting α_S from PDFs

- PDF parametrization may bias the α_S value.
- Correct treatment of experimental systematics (particularly normalization uncertainties).
- Hidden uncertainties in theoretical description of PDFs (e.g. heavy quark treatment).
- Inclusion of PDF uncertainty in the α_S determination.
- Accurate estimation of missing higher order uncertainties

Challenges extracting α_S from PDFs

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- Correct treatment of experimental systematics (particularly normalization uncertainties). [NNPDF]
- Hidden uncertainties in theoretical description of PDFs (e.g. heavy quark treatment). [NNPDF 3.1]
- Inclusion of PDF uncertainty in the α_S determination. [NNPDF 3.1- α_S]
- Accurate estimation of missing higher order uncertainties [TODO]

Made notable progress since latest NNPDF determination in 2011.

- α_S determination based on NNPDF3.1
- Can collider determinations of α_S be really independent on those from PDFs?
- Can we *measure* theoretical uncertainties?

Precision determination of the strong coupling constant within a global PDF analysis

NNPDF Collaboration, arxiv:1802.03398

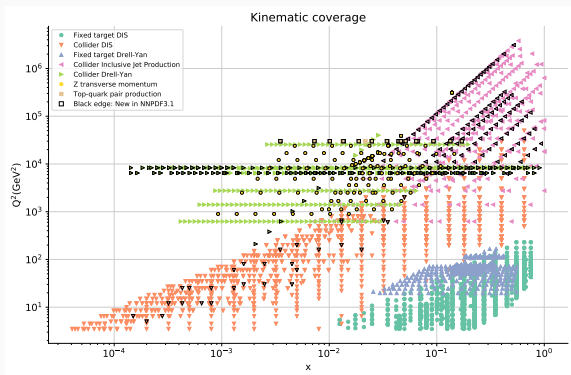
- 3979 data points.
- Including simultaneously differential top, $Z pT$ and inclusive jet data for the first time.
- Exact NNLO theory
- Method to effectively fit α_S and the PDF simultaneously (PDFs effectively nuisance parameters).

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Dataset in NNPDF 3.1



α_S dependence though:

- PDF evolution (large scale differences advantageous).
- Direct dependence (e.g. $t\bar{t}$ data)
- Higher order QCD corrections.

Propagating uncertainties in NNPDF

Our data has experimental uncertainties.

- We view the data as random variables from the distribution $\mathcal{N}(d_i, \Sigma_{i,j})$
 - d_i is the experimentally measured central value for the point i .
 - Σ_{ij} a covariance between the points i, j .
- We sample N_{rep} datasets (Monte Carlo pseudodata) from the distribution, and train neural networks “replicas” to each dataset to minimize an error function χ^2 .
- PDF dependent quantities are calculated from statistics over the ensemble of replicas. E.g. “PDF uncertainty” is usually the standard deviation over the replicas.

Simultaneous minimization of (α_S, PDF)

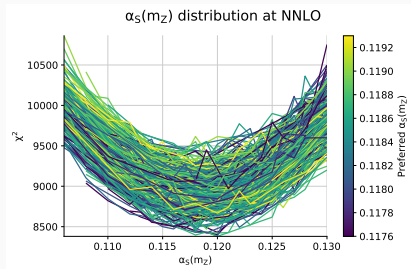
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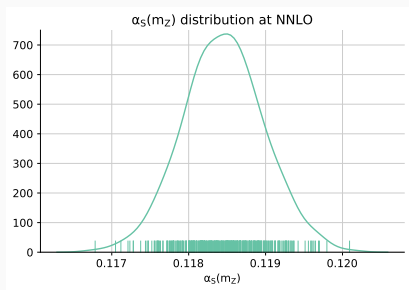
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 - Solution: Repeat the fit for discrete values of α_S to the same data replica \rightarrow c-replica.
- Each c-replica has a $\chi^2(\alpha_S)$ profile.
- Each minimum yields one sampled α_S value.



The result

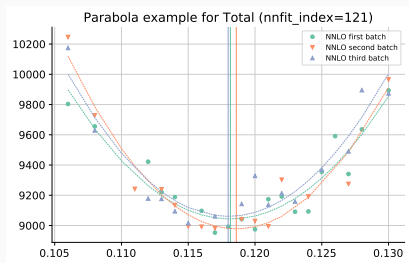
We obtain

$$\alpha_S^{\text{NNLO}}(M_Z) = 0.11845 \pm 0.00052^{(\text{exp})} (0.4\%)$$

- Experimental uncertainty is the standard deviation over the ensemble of c-replicas of the $\arg \min_{\alpha_S} \chi^2(\alpha_S)$.
- Very small uncertainty (compared to other determinations in the PDG). But need to assess:
 - Methodological systematics.
 - Theory uncertainties.

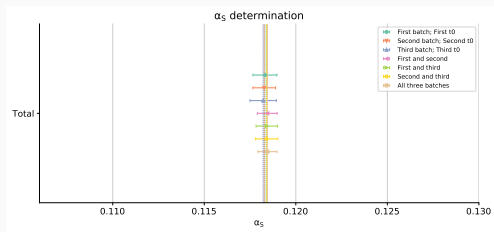
Improvement by batch minimization

- The NNPDF methodology discards replicas that do not meet certain convergence criteria (25-30%).
- $\chi^2(\alpha_s)$ noisy for each c-replica. Fit quality depends on:
 - Initial conditions.
 - Cross validation split
- Solution: Repeat each fit three times, and take the minimum (requiring at least 2 successful replicas).



Effect of batch minimization

- Small on central value $\sim O(0.4) \times \Delta^{(\text{exp})}$.
- Significant on uncertainty. Reduction to up to 27%.
- Convergence already good with two batches.



Finite-size uncertainties

We estimate the uncertainties due to fitting a finite number of replicas by bootstrapping.

1. Take the set of N minima.
 - 1.1 Sample with replacement from it M sets of N values, with M large.
 - 1.2 Compute the M means of each of the M sets.
 - 1.3 Compute the standard deviation of the M means.

$$\Delta_{\text{stat}} = 3 \times 10^{-5}$$

Effect negligible compared to the PDF uncertainty.

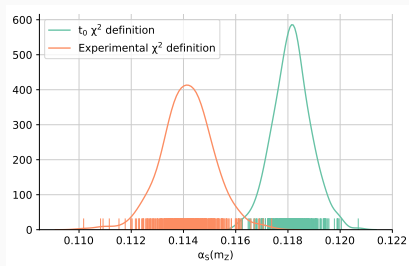
Curve selection

- Select c -replicas that contain at least N_{\min} successfully fitted values.
- Choose N_{\min} to minimize the bootstrapping uncertainty.
 - Tradeoff between statistics and quality of the parabolas.
- Result stable for reasonable values N_{\min} .

N_{\min}	$\alpha_s(m_Z)$	N_{rep}	Δ_{α_s}
18	0.11842 ± 0.00031 (0.3%)	12	0.00009
15	0.11844 ± 0.00044 (0.4%)	92	0.00005
6	0.11845 ± 0.00052 (0.5%)	379	0.00003
3	0.11844 ± 0.00056 (0.5%)	400	0.00003

Treatment of normalization uncertainties

- It is well known [D'Agostini, 2003] that minimizing the experimental χ^2 is biased in the presence of normalization uncertainties.
 - Maximum likelihood estimator is not an unbiased estimator.
- NNPDF uses the t_0 procedure [arxiv:0912.2276] (fix normalization from the result of a previous fit).
- α_S fit heavily biased when the experimental definition of χ^2 is used inconsistently to minimize α_S .



Final methodological uncertainty

- Checked many other possible sources of systematics.
 - Assumption that $\chi^2(\alpha_s)$ is parabolic.
 - Dependence on the extreme values.
 - Myriad of variations of replica selection.
 - Effect of t_0 procedure.
- Overall all effects much smaller than experimental uncertainty. Methodological effects conservatively estimated at $\sim 10^{-4}$ (0.09%).

Theoretical uncertainties that are under control

- Theoretical effects necessarily have to affect the PDFs in order to affect our determination.
- But not sufficient: Dependence on $\alpha_S(M_Z)$ required.
- Many have been studied and found to be smaller than experimental uncertainties:

Higher twist found to be small compared to experimental uncertainties [arxiv:1303.1189].

Charm mass greatly improved by parameterizing the charm PDF [arXiv:1605.06515].

Electroweak corrections Kept under control with suitable cuts [arxiv:1706.00428].

Nuclear corrections Studied in [arxiv:1706.00428] and found to be small compared to experimental uncertainties.

In conclusion **MHOU highly likely to be the dominant theoretical uncertainty.**

Estimates of MHOU

No reliable method known for PDF based quantities. We have:

$$\alpha_S^{\text{NNLO}}(M_Z) = 0.1184 \pm 5 \times 10^{-4}$$

$$\alpha_S^{\text{NLO}}(M_Z) = 0.1206 \pm 6 \times 10^{-4}$$

- PDF fits with scale variations currently in early stage.
- Methods based on continuation of perturbative series such as Cacciari-Houdeau [arXiv:1105.5152] hampered by:
 - Poor fit quality at LO and even at NLO.
 - Lack of unique series expansion (many processes involved).
- CH yields a theoretical uncertainty of 4×10^{-4} , smaller than the experimental ones. Likely too optimistic.

Final MHO estimate

For lack of better options, make it be crude and conservative.

$$\Delta\alpha_S^{\text{th}} = \frac{1}{2} |\alpha_S^{\text{NLO}} - \alpha_S^{\text{NNLO}}| = 0.0011(0.9\%)$$

- Uncertainty likely overblown by the poor fit quality at NLO.

	$\min_{\alpha_S} \chi^2(\alpha_S^{\text{(central)}})/N_{\text{data}}$
NLO	5014/3979=1.26
NNLO	4814/3979=1.21

- Two times bigger than the experimental uncertainty.

There must be a better way! A data driven way?

Let us make the following assumptions:

- Data entering the fit can be separated in *processes* where MHOUs are largely uncorrelated.
 - In practice correlations expected because of the PDF.
 - Also must see how to deal with experimental correlations.
- One can define a preferred value of α_S for each process somehow.
- There are sufficient number of processes to make statistics.
- Differences in preferred values above experimental uncertainties are due to theoretical differences.

It follows that theoretical uncertainties can be estimated through the dispersion of the preferred values.

- Strong assumptions, but is it really worse than scale variations?

How NOT to define preferred values: The partial χ^2

The global χ^2 minimizes to fit (α_S, PDF) looks like

$$\chi^2 [\{\theta\}, \alpha_S, \mathcal{D}] = \sum_{l,j=1}^{N_{\mathcal{D}}} (T_l[\{\theta\}, \alpha_S] - D_l) C_{lj}^{-1} (T_j[\{\theta\}, \alpha_S] - D_j)$$

where

- $\{\theta\}$ are the parameters of the PDF.
- \mathcal{D} is the set of $N_{\mathcal{D}}$ data points entering the fit.
- T_l is the theoretical prediction for the data point indexed by l .
- D_l is the experimentally measured value.
- C_{lj} measures the experimental covariance.

The profile of a c-replica is

$$\chi^2(\alpha_S) = \min_{\{\theta\}} \chi^2 [\{\theta\}, \alpha_S, \mathcal{D}]$$

Definition of partial χ^2

The partial χ^2 is:

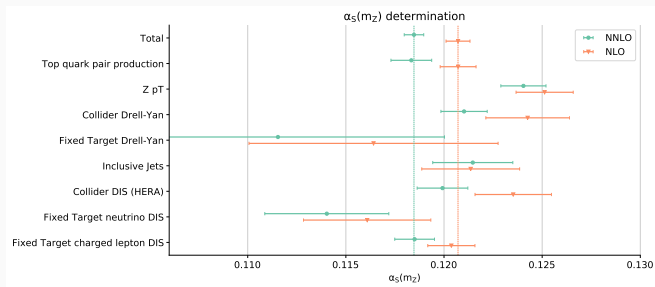
$$\chi_p^2[\{\theta\}, \alpha_s, \mathcal{P}] = \sum_{I,J=1}^{N_{\mathcal{P}}} (T_I[\{\theta\}, \alpha_s] - D_I) C_{IJ}^{-1} (T_J[\{\theta\}, \alpha_s] - D_J)$$

where we have replaced \mathcal{D} with \mathcal{P} , a subset of \mathcal{D} with $N_{\mathcal{P}}$ points, and neglected the correlations between the points in \mathcal{P} and \mathcal{D} .

- Up to missing correlations, for a set of processes that cover all \mathcal{D}

$$\chi^2(\alpha_s) = \sum_p \chi_p^2(\alpha_s)$$

Results from partial χ^2



- Define

$$\alpha_s^p = \arg \min_{\alpha_s} \chi_p^2(\alpha_s)$$

- Useful to estimate pulls qualitatively. E.g. can say that the LHC data likely contributes to increase $\alpha_s(M_Z)$.
- But quantitative calculations are seriously off.

Partial χ^2 and α_S determination from hadronic processes

By “collider determinations” I mean determinations of α_S based on cross sections measured at hadron–hadron and hadron–lepton colliders that are used to constrain the strong coupling independently of a PDF fit.

G.Salam [arxiv:1712.05165]

However all “collider determinations” in practice amount to the partial χ^2 minimization above. Collider determinations depend on the PDF in two ways:

- Best fit PDF changes strongly with α_S , i.e.
 $\{\theta\}(\alpha_S) = \arg \min_{\{\theta\}} \chi^2(\alpha_S, \{\theta\}, \mathcal{D})$.
- Global fit quality $\chi^2(\alpha_S)$ changes strongly with α_S .

- Notable example CMS measurement of $t\bar{t}$ [arXiv:1307.1907] computed at NNLO [Czakon, Fiedler, Mitov, arXiv:1303.6254] included in the PDG average as the only item in the collider determination category.
- Many others have appeared recently. For example, a determination using jets in DIS at NNLO [H1 Collaboration arxiv:1709.07251] at. The result, using NNPDF3.1 sets, is $\alpha_S = 0.1157 \pm 0.002^{\text{exp}} \pm 0.003^{\text{th}}$. The central value is discarded by the NNPDF3.1 determination at 5σ .

Problems with the partial χ^2

- Neglecting correlations is a bad approximation.

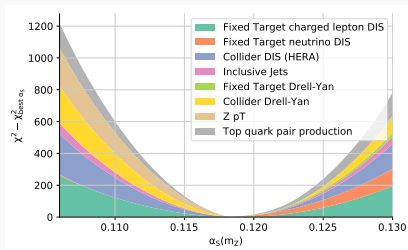
$$\alpha_S^{(\text{global})} - \arg \min_{\alpha_S} \sum_p \chi_p^2(\alpha_S) \sim \text{std}_p \alpha_S^p$$

Deviation of the order of the quantity we wanted to estimate.

- By construction it doesn't take into account the global fit quality [Z.K, arxiv:1802.05236].
- Preferred values extracted this way amount to a logical contradiction:
 - Choose a point in the phase space $(\alpha_S^p, \underbrace{\arg \min_{\{\theta\}} \chi^2(\{\theta\}, \alpha_S^p, \mathcal{D})}_{\text{best fit PDF at } \alpha_S^p}),$
 - discarded by the data $(\mathcal{D}),$
 - used to construct constrain the PDF parameters $\{\theta\},$
 - on which α_S^p relies in the first place.

Fit results outside the global best fit

- χ_p^2 depends strongly on the rest of the data entering the fit.
- χ_p^2 inversely correlated to relative weight of \mathcal{P} (given by the number of points). The more weight \rightarrow the more advantageous it is to optimize for it at the expense of some other data \rightarrow the smaller χ_p^2 .
- For example, note $t\bar{t}$. 26 points (0.6% of the total) are only described simultaneously with the rest of the data in a small range of α_S values.



Importance of simultaneous minimization

Can it be that for processes like $t\bar{t}$, $\chi_p(\alpha_S)$ changes much more quickly than the global $\chi^2(\alpha_S)$. Made an experiment to test it:

- The further away from the global minimum, the larger the space of PDs with the same $\chi^2(\alpha_S)$.
- Can alter the fit in a way that changes substantially χ_p^2 and very little the global χ^2 .
- Set up:
 - Take the 26 points of $t\bar{t}$ data and copy them 15 times in a fit at $\alpha_S(M_Z) = 0.121$. The target function becomes $\chi'^2 = \chi^2 + 14\chi_{t\bar{t}}^2$.
 - Now $t\bar{t}$ has more weight in the fit.

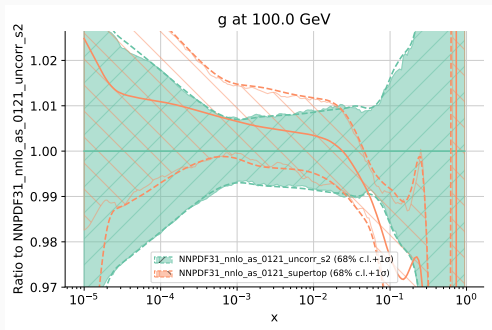
Results of reweighted fit

$\chi^2/d.o.f.$	$\alpha_S = 0.118$	$\alpha_S = 0.121$ default	$\alpha_S = 0.121$ weighted $t\bar{t}$
Total	1.162	1.212	1.228
$t\bar{t}$	1.07	1.42	1.02

- Very small change in the total χ^2 .
- Can bend the PDF to describe the top data perfectly at a larger value of α_S .

Changes in the PDFs

- Bigger α_s compensate with smaller gluon PDF in the relevant kinematic region.



- Still compatible within uncertainties.
- Rest of PDFs largely unchanged.
- **Conclusion:** $t\bar{t}$ determination not independent on PDFs.

An even more convincing example

- It turns out that in our analysis the minimum for χ_{tt}^2 ($\alpha_S(M_Z) = 0.1183$) is very close to the global minimum $\chi^2(\alpha_S(M_Z) = 0.11845)$.
- Selecting a different process, we can engineer a fit where both χ_p^2 and χ^2 are lower than for the minimum of the partial χ^2 .
- For ZpT we have $\alpha_S^{ZpT} \approx 0.124$ in the default fit.
- Assign the 120 points of ZpT data a weight of 32 (this makes it weight as much as the rest of the data).

Results of $Z pT$ weighted fits

$\chi^2/d.o.f.$	$\alpha_s = 0.120$ weighted $Z pT$	$\alpha_s = 0.124$ default
Total	1.226	1.281
$Z pT$	0.94	1.11

The weighted fit agrees better both with the whole ensemble \mathcal{D} and the $Z pT$ data. It is therefore a better value of α_s from $Z pT$, no matter how you look at it.

- I consider this a proof that the partial χ^2 minimization entails a logical contradiction, since in principle it is possible to find a better fit.

Coming back to theoretical uncertainties

- We could exploit similar weighting strategy to define dataset dispersion [Z.K. arxiv:1802.05236].
- Associate a large enough weight to each dataset to force $\chi_p^2(\alpha_S)/d.o.f. \simeq 1$ (statistical minimum when cross validation is applied) in a large range of α_S .
- Define preferred value as the one where the rest of the data agrees the best, i.e. $\alpha_S^{(\text{preferred } p)} = \min_{\alpha_S} \chi^2(\alpha_S)^{(\text{weighted } p)}$.

Advantages of definition of preferred value

- Ideally defined as best fit to all the data, restricted to describing perfectly the specific dataset (weight is an implementation detail).
- Explicitly depends on all the data in the problem \mathcal{D} .
- Dispersion of preferred values over datasets (above experimental uncertainties) can be interpreted as mainly coming from theory.
- Possible formula

$$\Delta^{th} = \Delta^{exp} \frac{1}{N_p - 1} \sqrt{\sum_p \frac{(\alpha_s - \alpha_s^{(preferred,p)})^2}{\frac{1}{2}(\Delta^{2,exp} + \Delta^{2(exp,preferred,p)})}}$$

Conclusions

- Determinations of α_S from global QCD fits (i.e. PDFs) have interesting characteristics to constrain its value.
- “Collider determinations” are flawed, and not independent on PDFs. Should not be used for World averages.
- It is interesting to explore data driven methods to study theory uncertainties, e.g. the dataset dispersion outlined here.

Thank you!