

JAM multi-step strategy

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A.I. for Nuclear Physics Workshop

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Motivation

- Traditionally different types of collinear distributions (PDFs, FFs) are obtained from independent analyses.
- Performing **simultaneous** fits of different collinear distributions allows us to:
 - Study the limits in x and Q^2 of collinear factorization
 - Test the universality of PDFs, FFs...
 - Extract the distributions in a **rigorous** way where all the data are studied using the **same** theoretical framework
- In this talk: (first) **simultaneous** analysis of **unpolarized PDFs** and FFs → **Strange** quark distribution

Evolution of JAM

	JAM15	JAM16	JAM17	JAM19	JAM20?
Process					
DIS	✓	✗	✓	✓	✓
DY	✗	✗	✗	✓	✓
SIA	✗	✓	✓	✓	✓
SIDIS	✗	✗	✓	✓	✓
					+ More processes
Function					
f	✗	✗	✗	✓	✓
Δf	✓	✗	✓	✗	✓
D_f^h	✗	✓	✓	✓	✓

Evolution of JAM

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DIS	✓	✗	✓	✓	✓
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SIDIS	✗	✗	✓	✓	✓
+ More processes					
Function					
f	✗	✗	✗	✓	✓
Δf	✓	✗	✓	✗	✓
D_f^h	✗	✓	✓	✓	✓

First **simultaneous** analysis of **unpolarized** PDFs and FFs

Evolution of JAM

	JAM15	JAM16	JAM17	JAM19	JAM20?
Process	✓	✗	✓	✓	✓
	✗	✗	✗	✓	✓
SIA	✗	✓	✓	✓	✓
SIDIS	✗	✗	✓	✓	✓
					+ More processes
Function	✗	✗	✗	✓	✓
f	✗	✗	✗	✓	✓
Δf	✓	✗	✓	✗	✓
D_f^h	✗	✓	✓	✓	✓

First **simultaneous** analysis of **unpolarized** PDFs and FFs

Why JAM19?

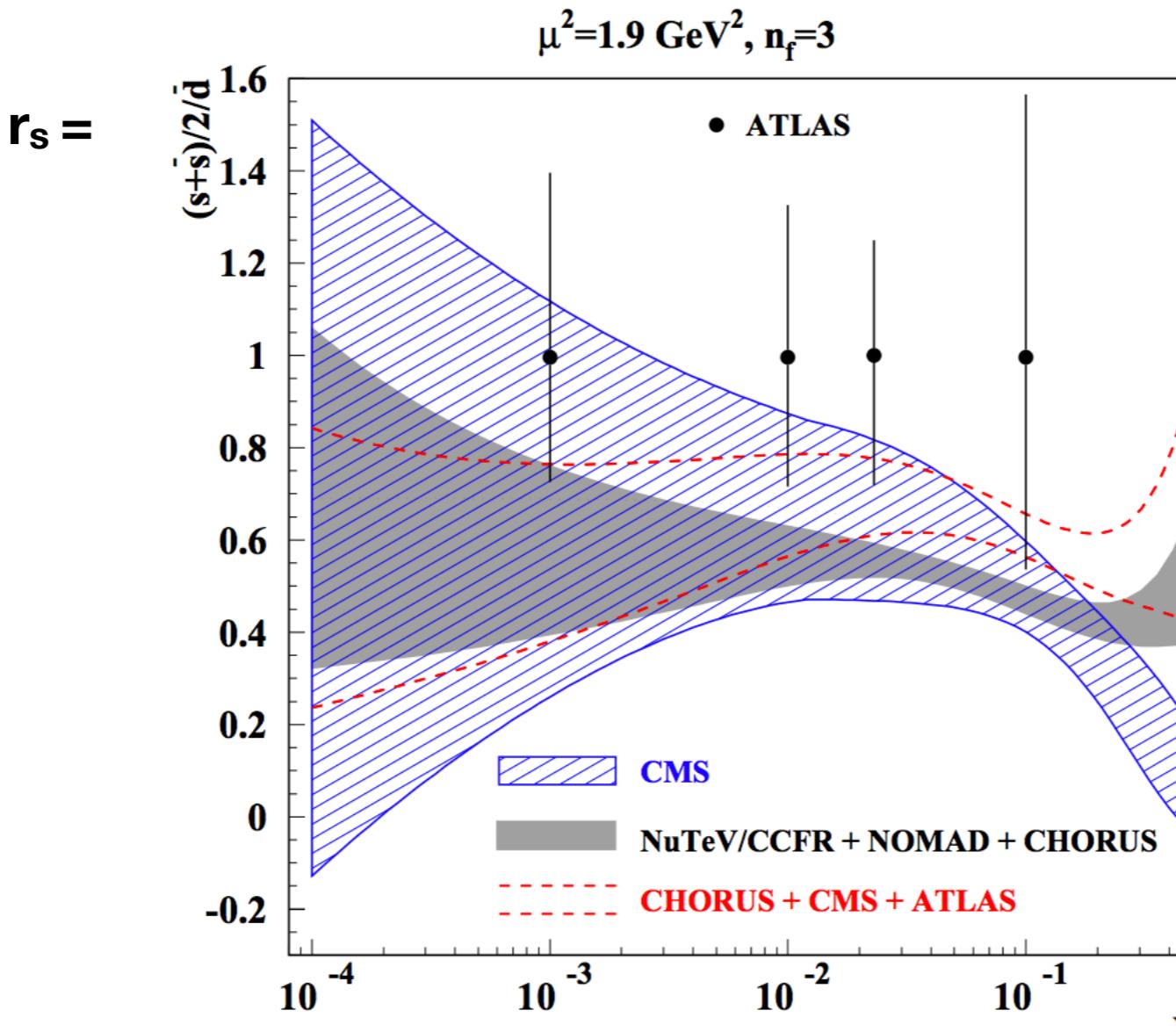
To study the **strange** quark distribution

Motivation II

- The strange PDF is **less known** than the non-strange light flavors
- Traditionally: neutrino-(heavy) **nucleus** DIS data used to extract the strange PDF.
 - Drawbacks: nuclear effects on PDFs.
- **W** and **Z** inclusive production in **p-p** collisions also sensitive to flavor separation
 - Drawbacks: tension between CMS and ATLAS results?

Motivation II

Alekhin et al. arXiv:1404.6469 [hep-ph]



First challenge: a wide variety of data

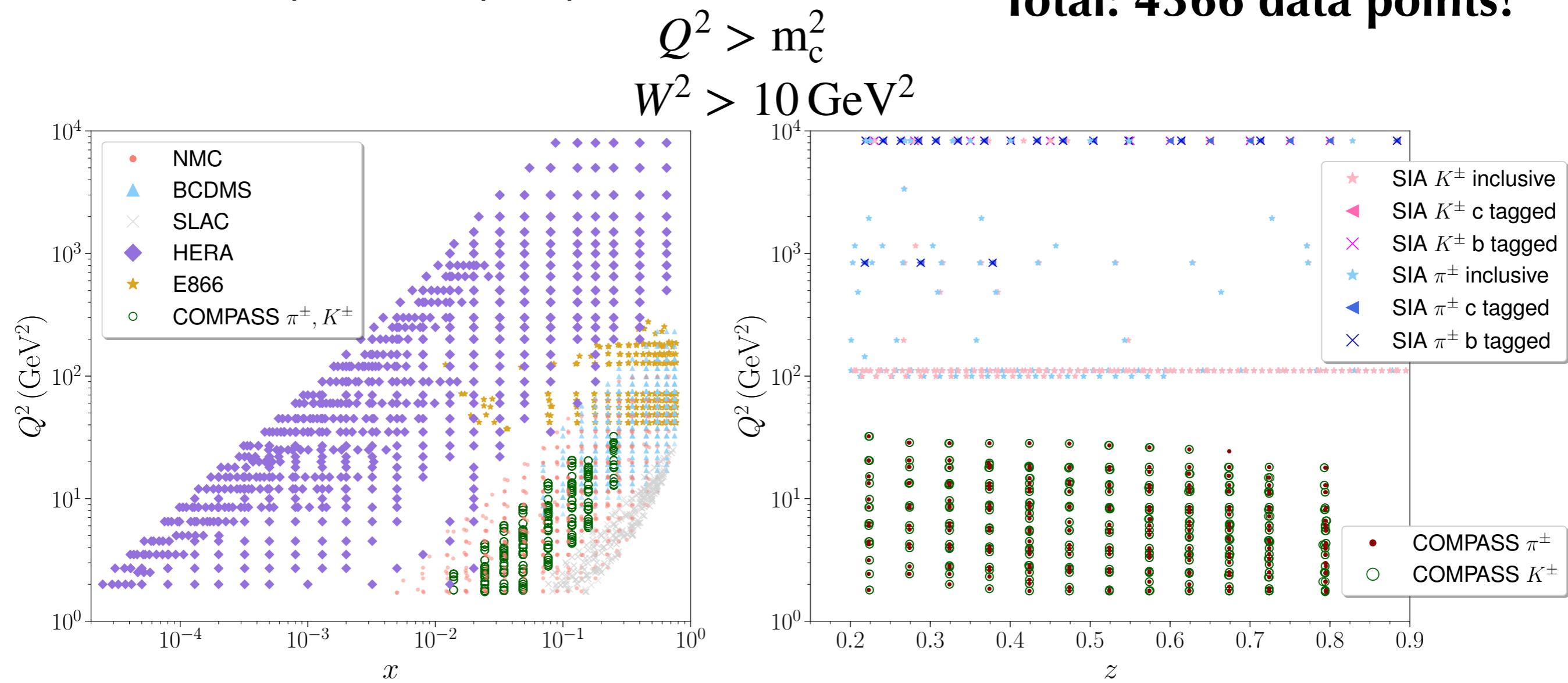
DIS : $l + (p, d) \rightarrow l' + X$

DY : $l + (p, d) \rightarrow l\bar{l} + X$

SIDIS : $l + d \rightarrow l' + h + X$

SIA : $e^+ + e^- \rightarrow h + X$

Total: 4366 data points!



Second challenge: MC fits

- Typical PDF parametrization:

$$x\Delta f(x) = Nx^a(1-x)^b(1+c\sqrt{x}+dx)$$

$$\chi^2 = \sum_e \sum_i^{N_{exp} N_{data}} \frac{(D_i^e - T_i)^2}{(\sigma_i^e)^2}$$

- Perform single χ^2 -fit:  Multiple local minima!

Parameters difficult to constrain

Hessian method for uncertainties  Introduces tolerance criteria

Unsuitable for simultaneous analysis of collinear distributions

- Monte Carlo methods:

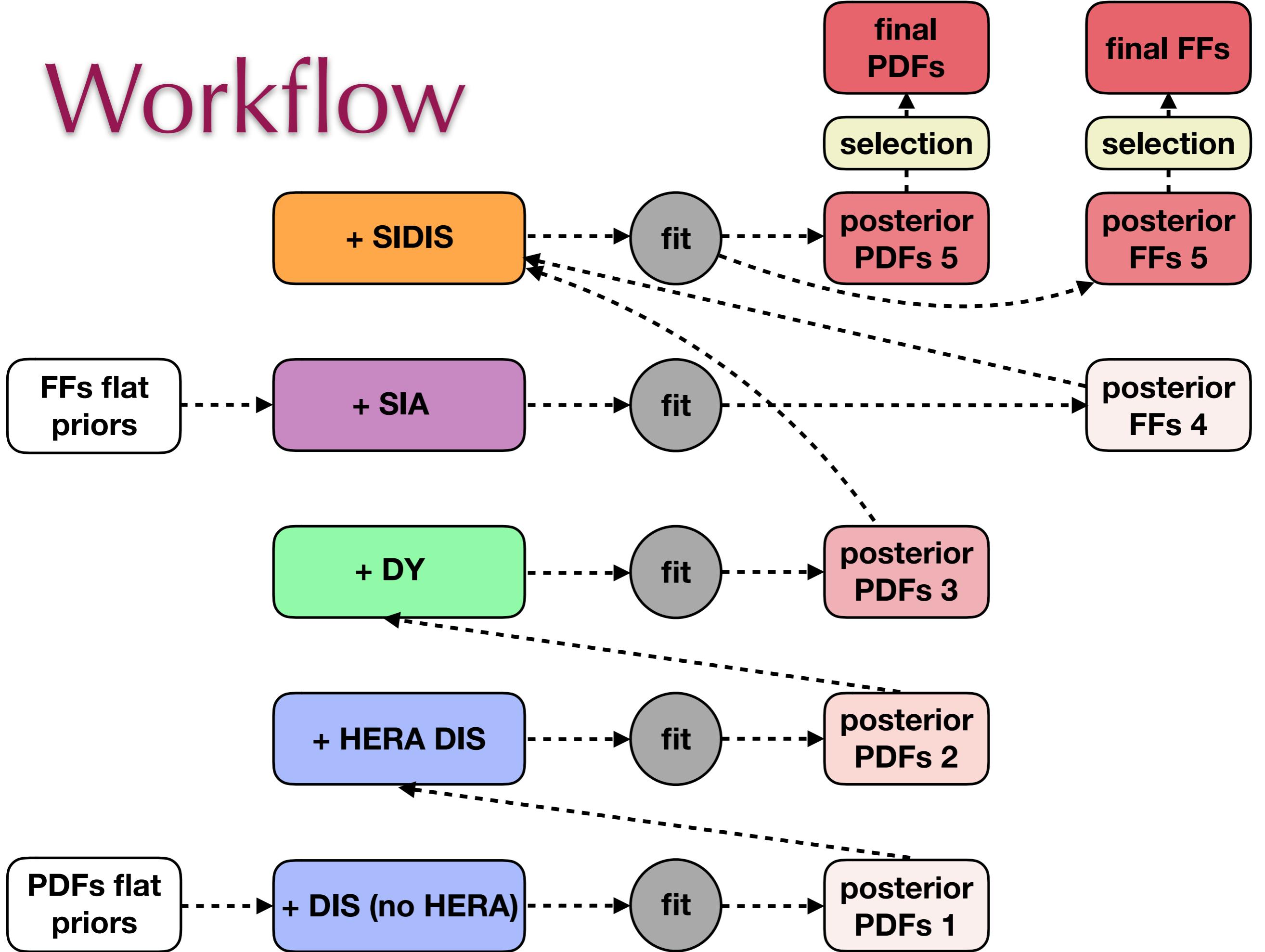
- Allow efficient exploration of the parameter space
- Uncertainties directly obtained from MC replicas

JAM19

multi-step

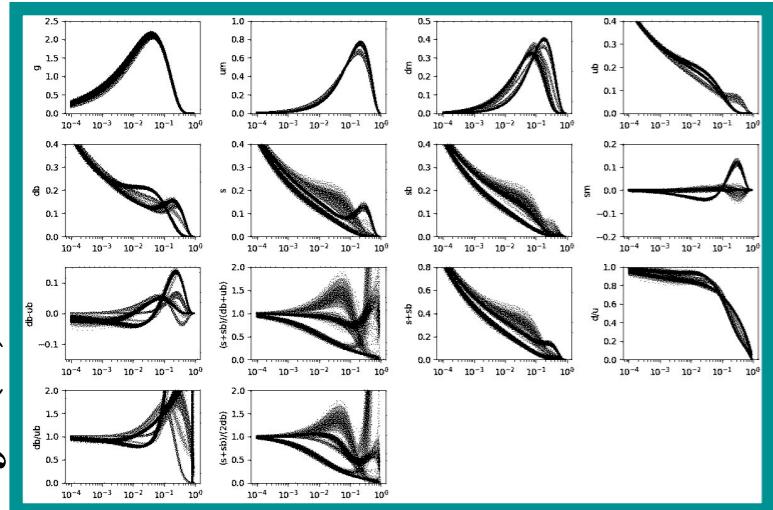
methodology

Workflow



JAM19: multi-step fitting

PDFs

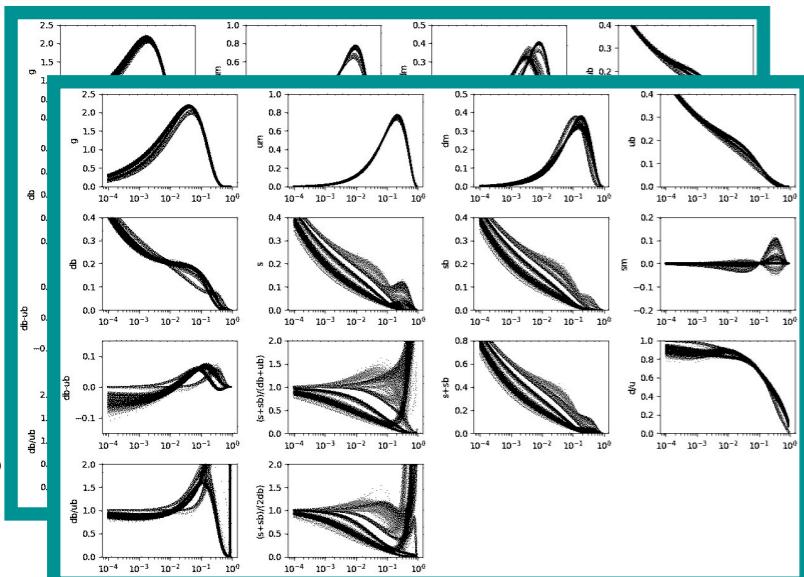


x

+ DIS data

JAM19: multi-step fitting

PDFs



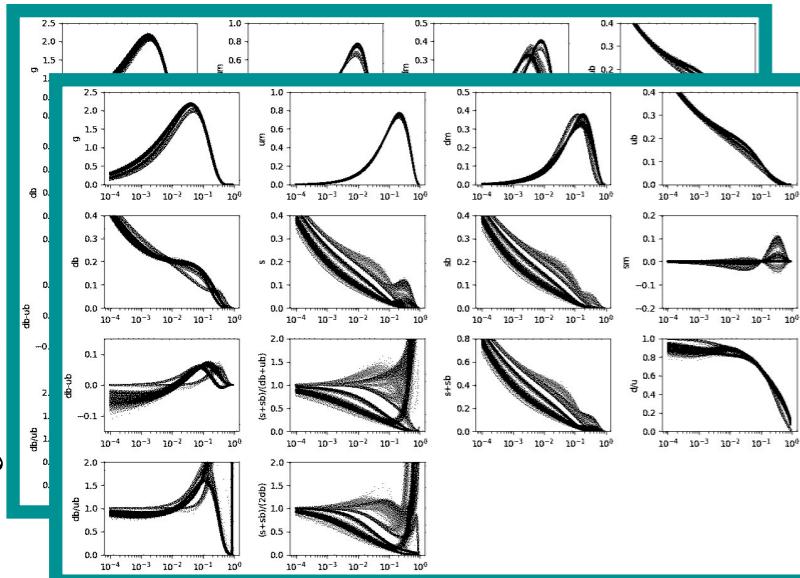
x

+ DIS data

+ DIS + DY data

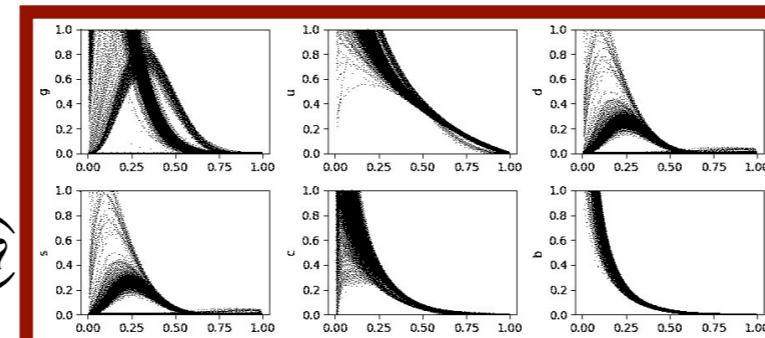
JAM19: multi-step fitting

PDFs



PION FF

$x f(x)$



Z

x

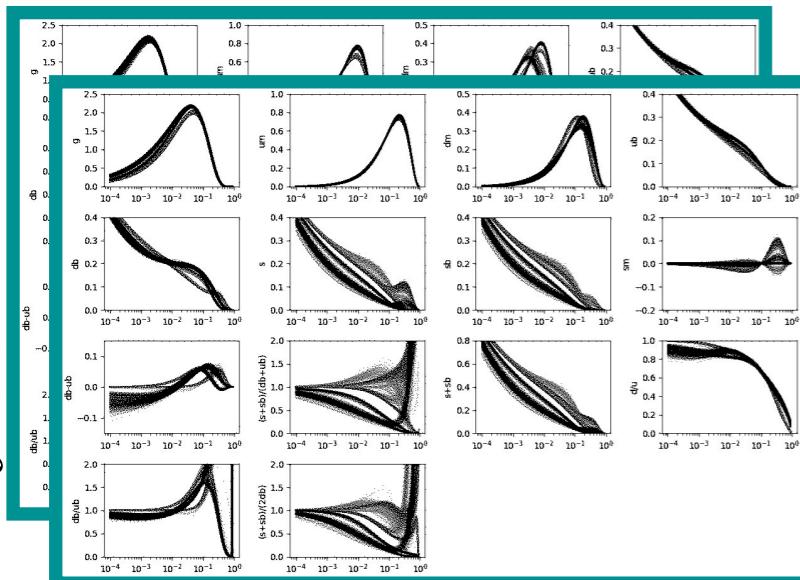
+ DIS data

+ SIA pion data

+ DIS + DY data

JAM19: multi-step fitting

PDFs



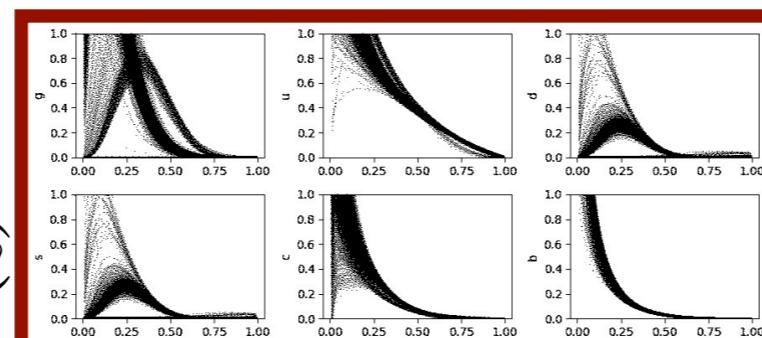
$x f(x)$

x

+ DIS data

+ DIS + DY data

PION FF

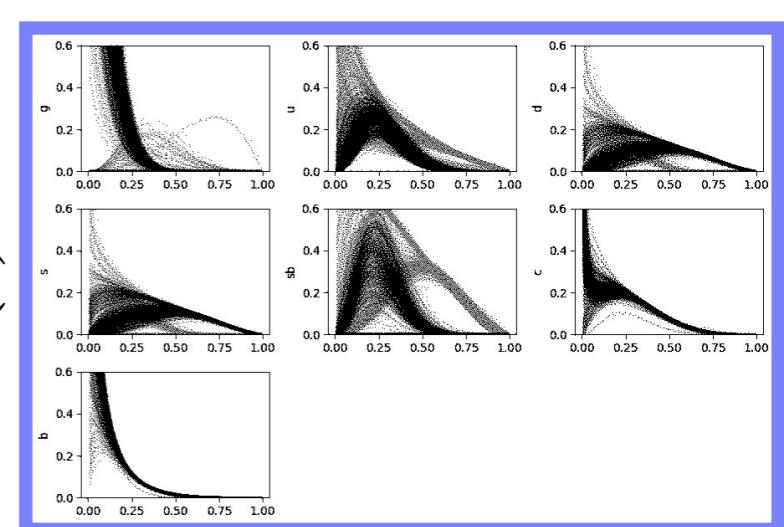


$z D(z)$

z

+ SIA pion data

KAON FF



$z D(z)$

z

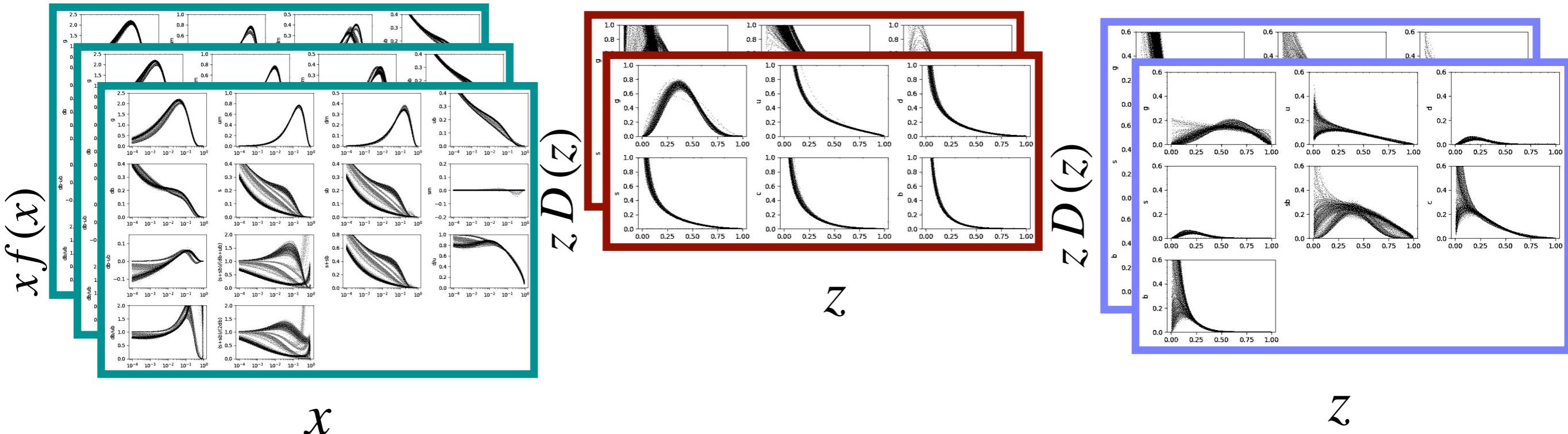
+ SIA kaon data

JAM19: multi-step fitting

PDFs

PION FF

KAON FF



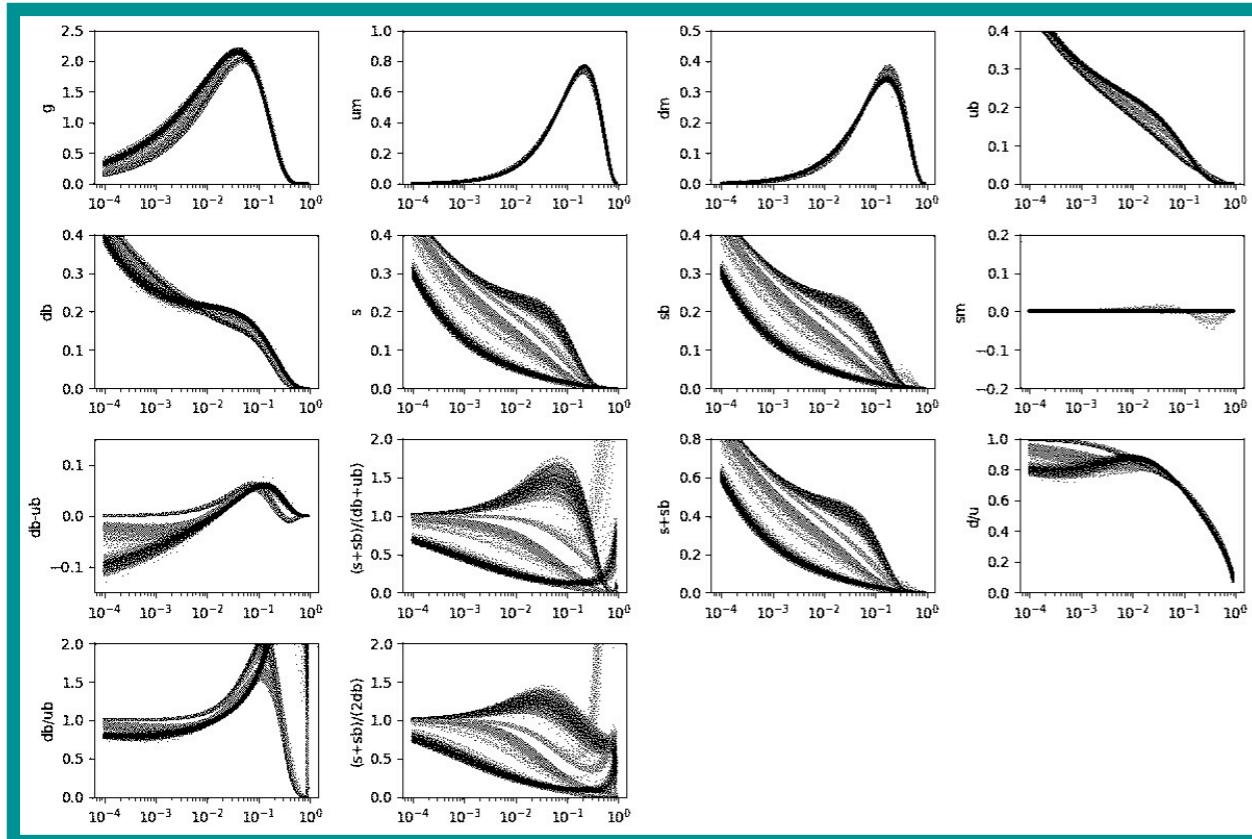
- + DIS data
- + DIS + DY data
- + SIDIS data

- + SIA pion data
- + SIDIS pion data

- + SIA kaon data
- + SIDIS kaon data

Discriminating multiple solutions

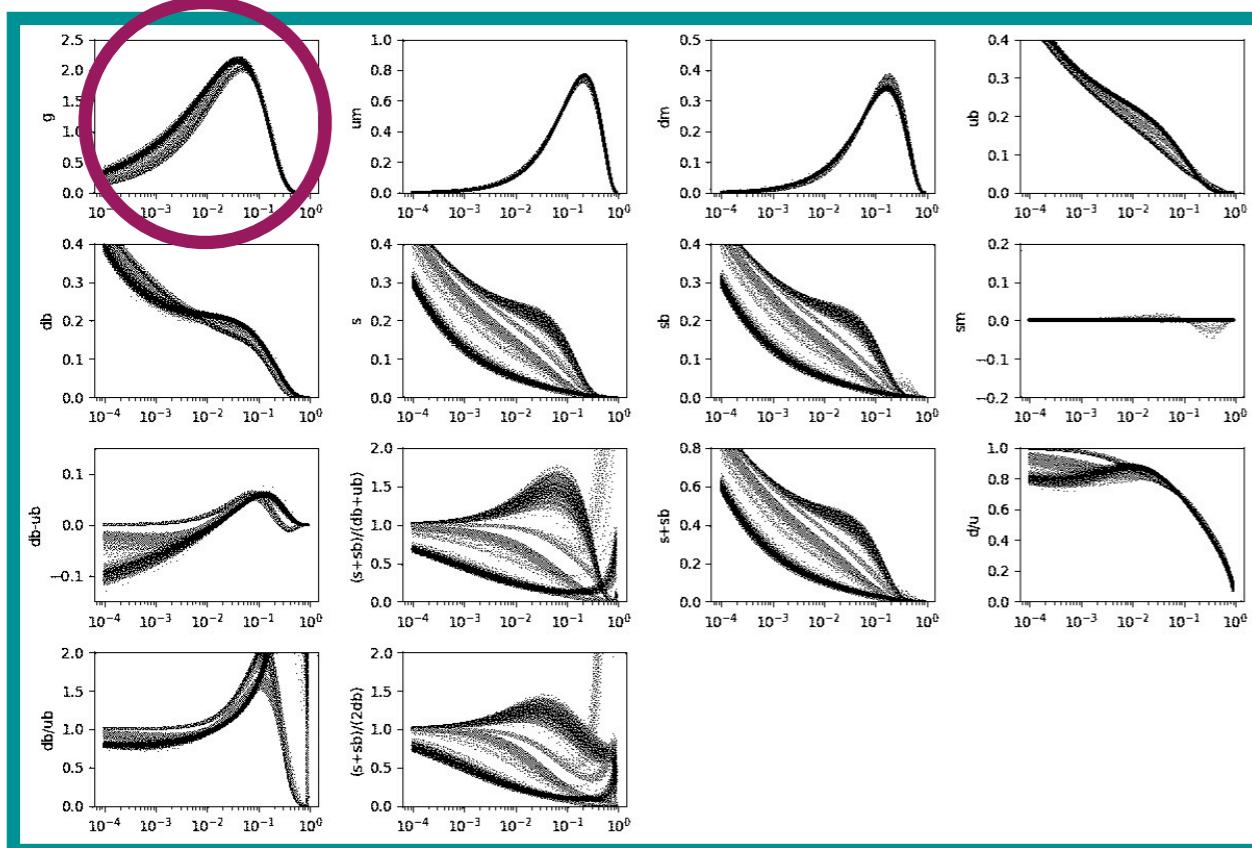
$x f(x)$



x

Discriminating multiple solutions

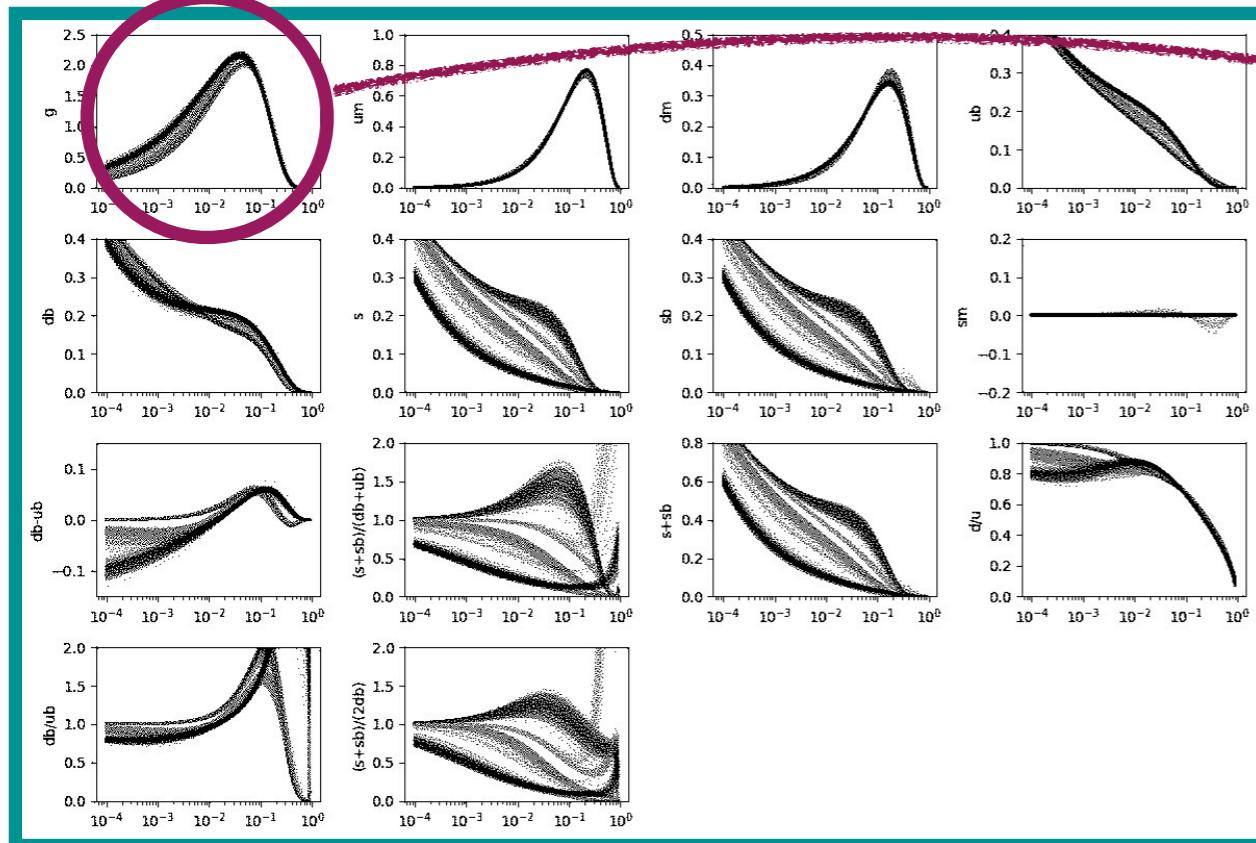
$x f(x)$



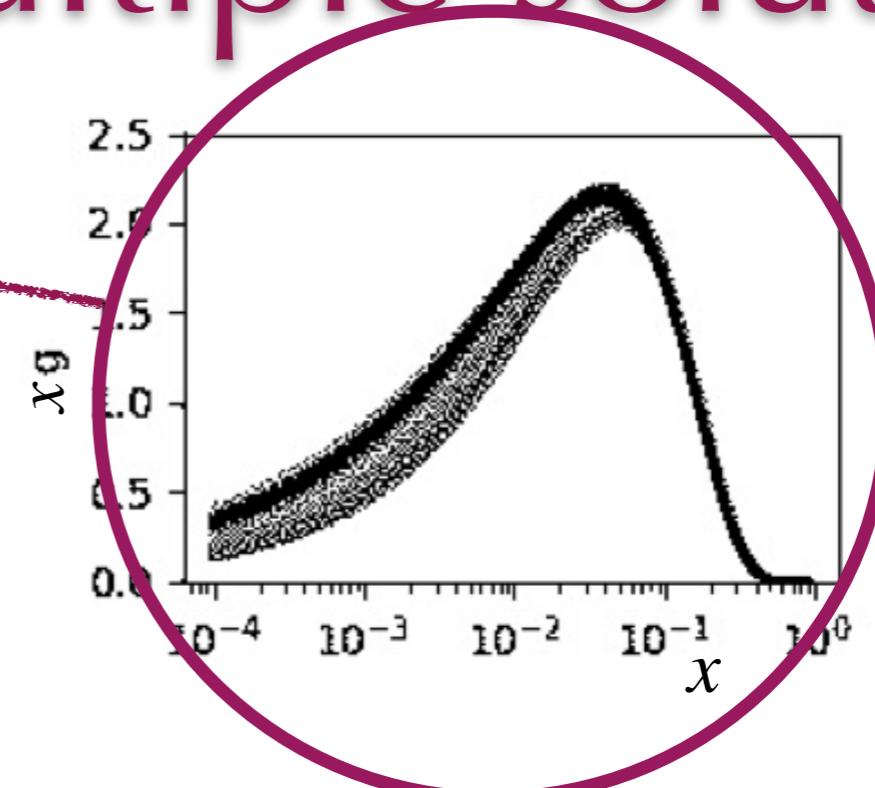
x

Discriminating multiple solutions

$x f(x)$

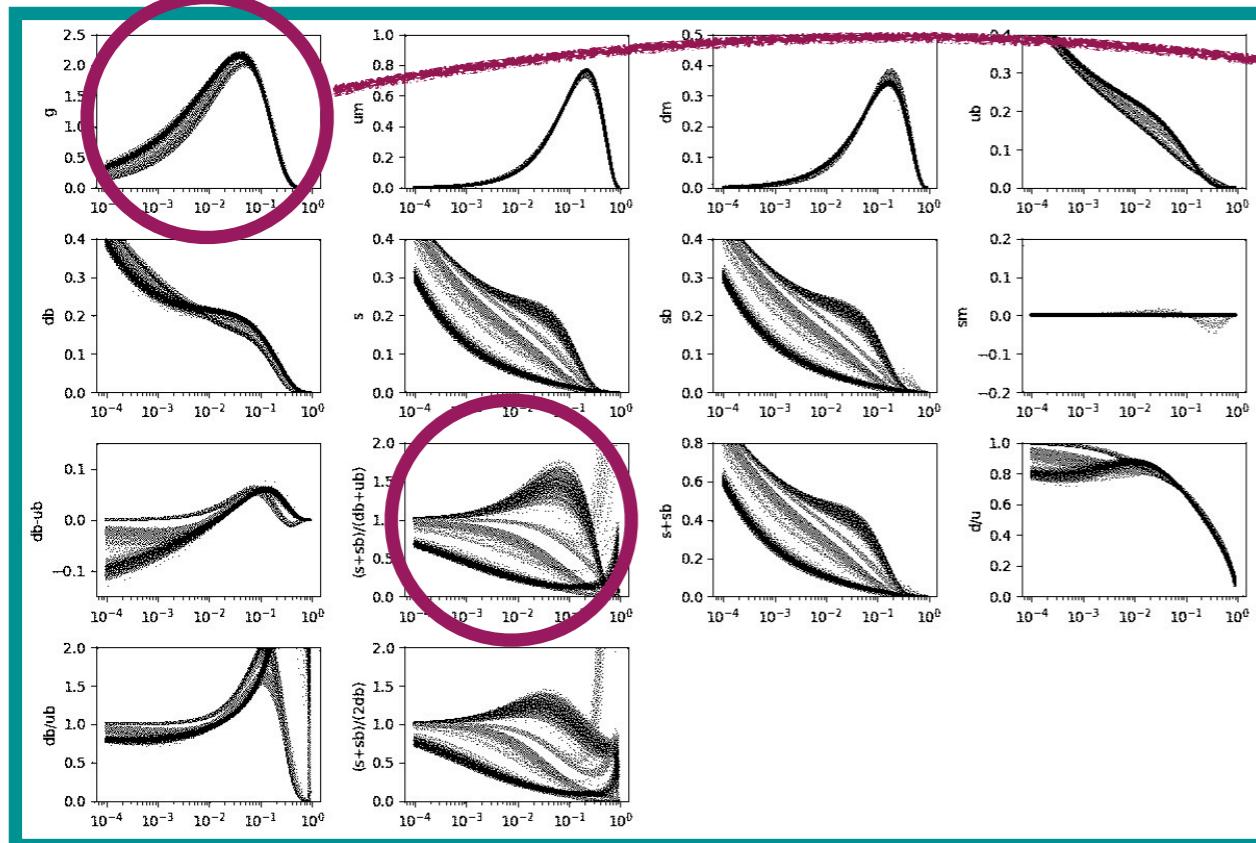


x

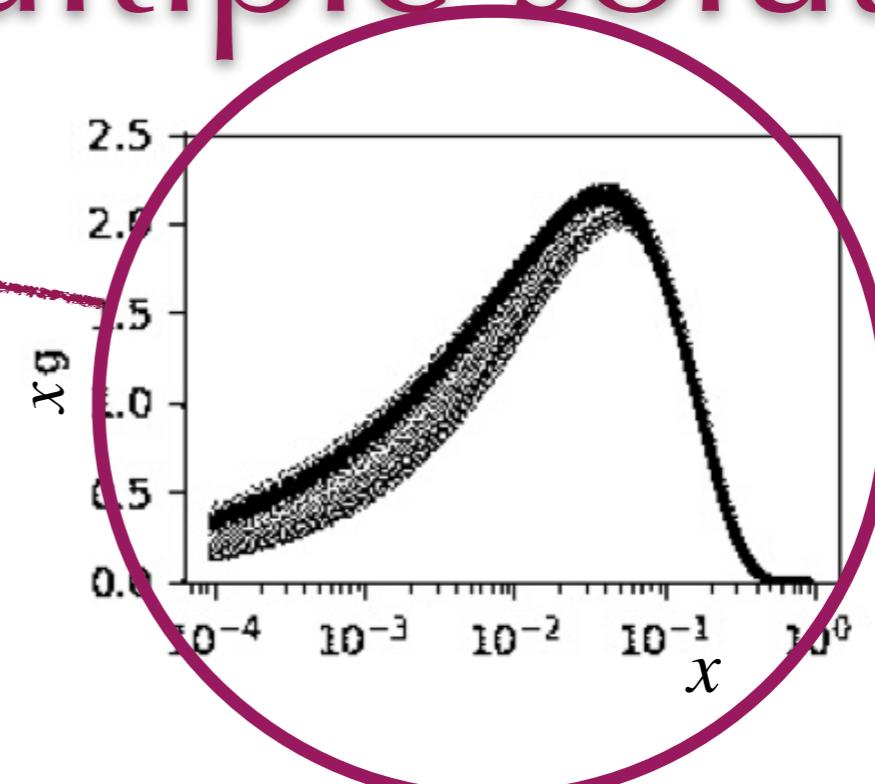


Discriminating multiple solutions

$x f(x)$

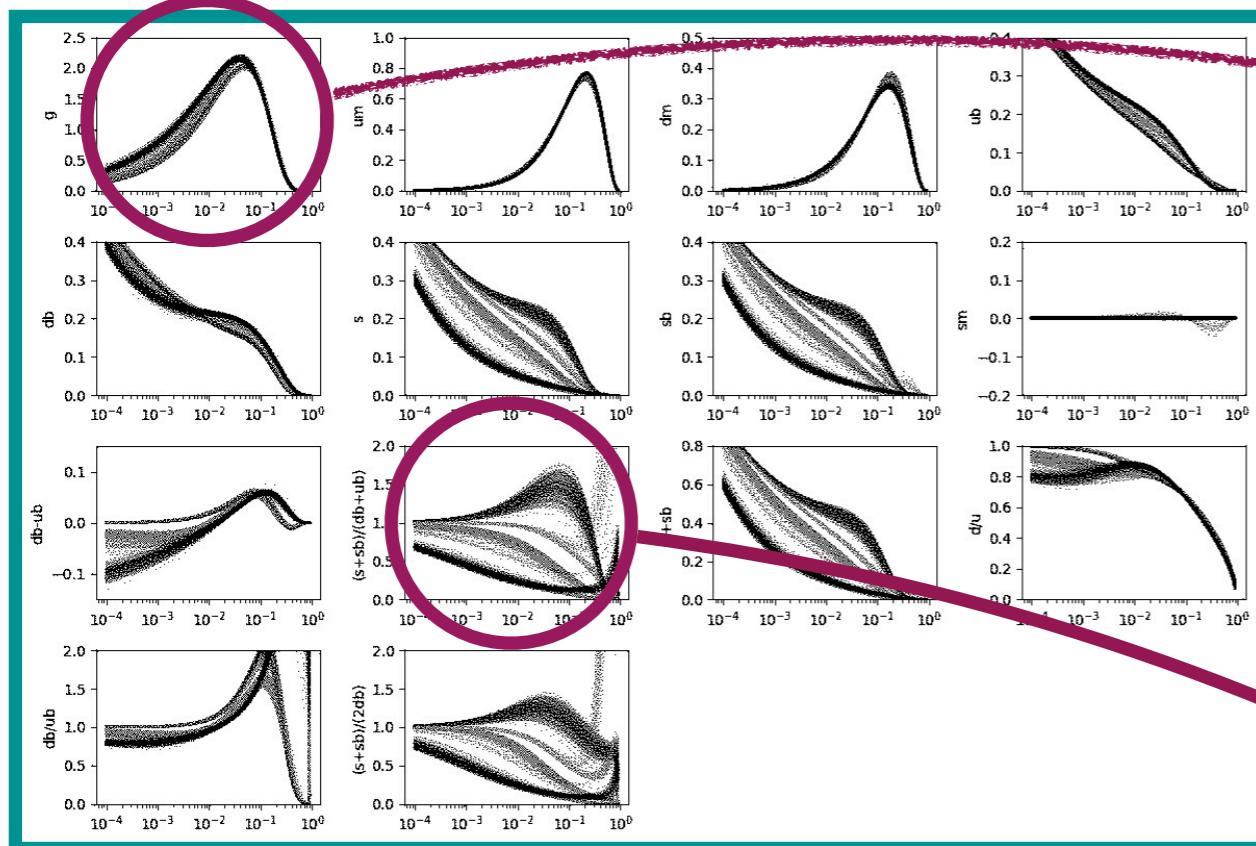


x



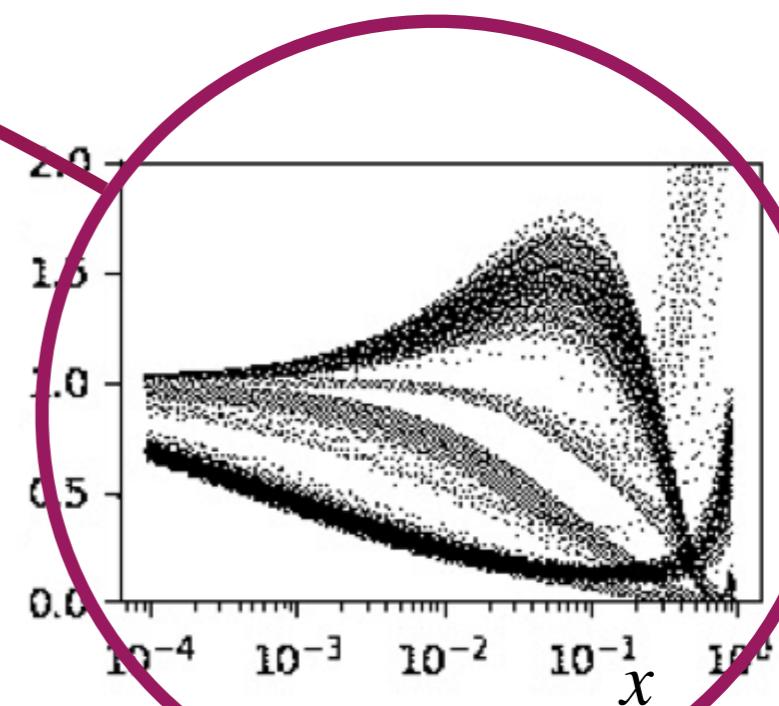
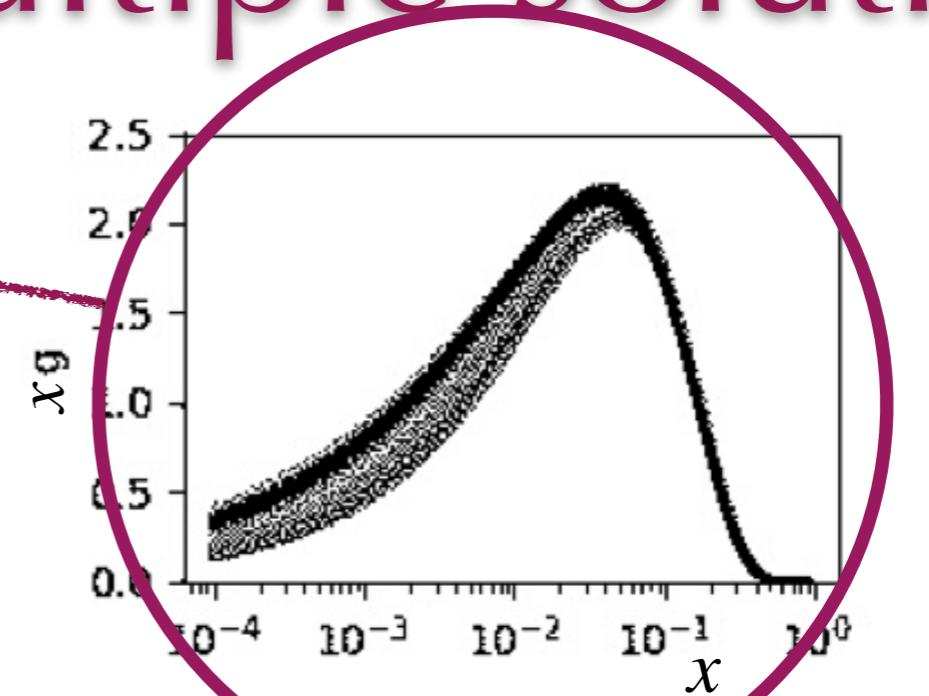
Discriminating multiple solutions

$x f(x)$



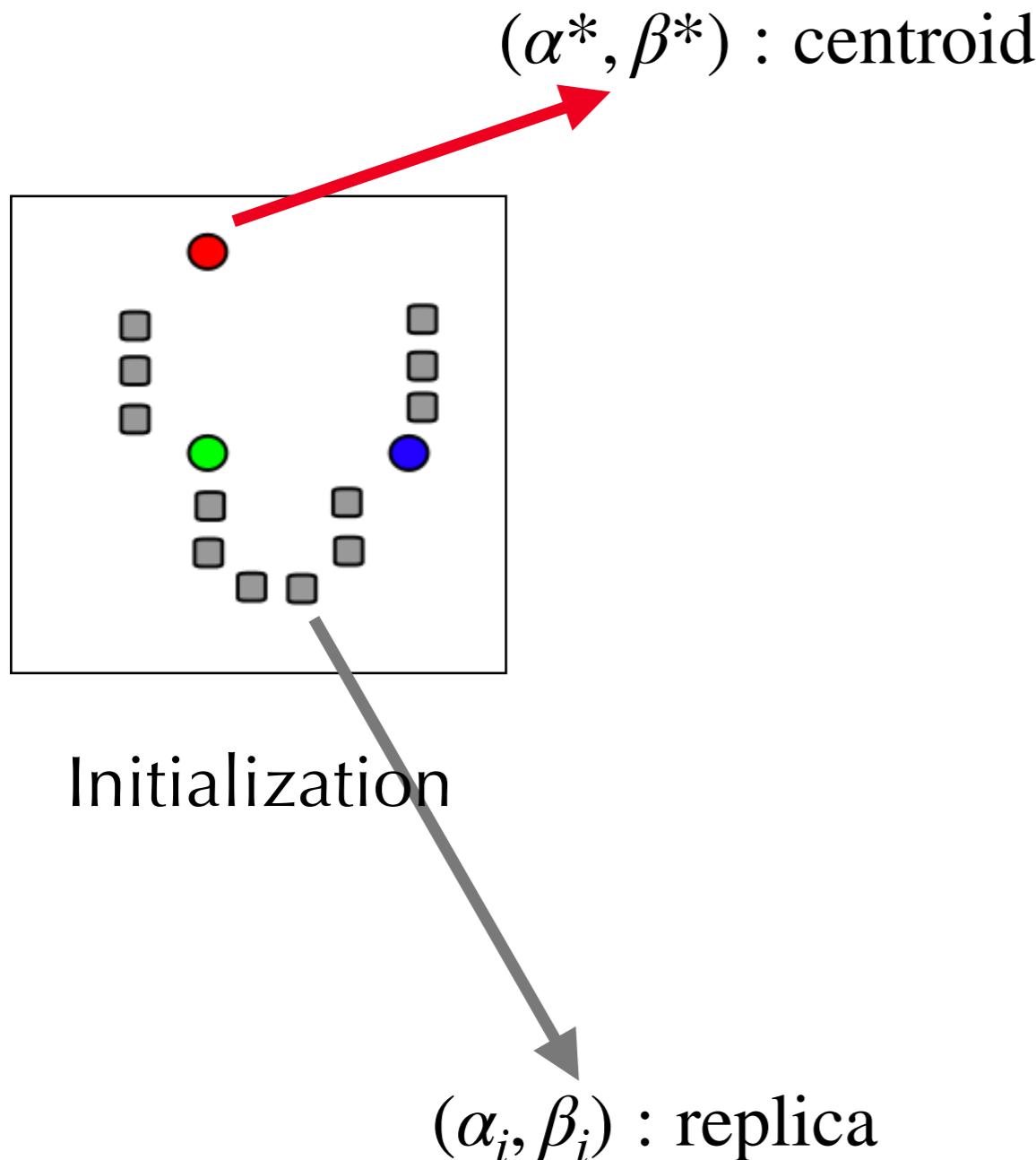
x

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$



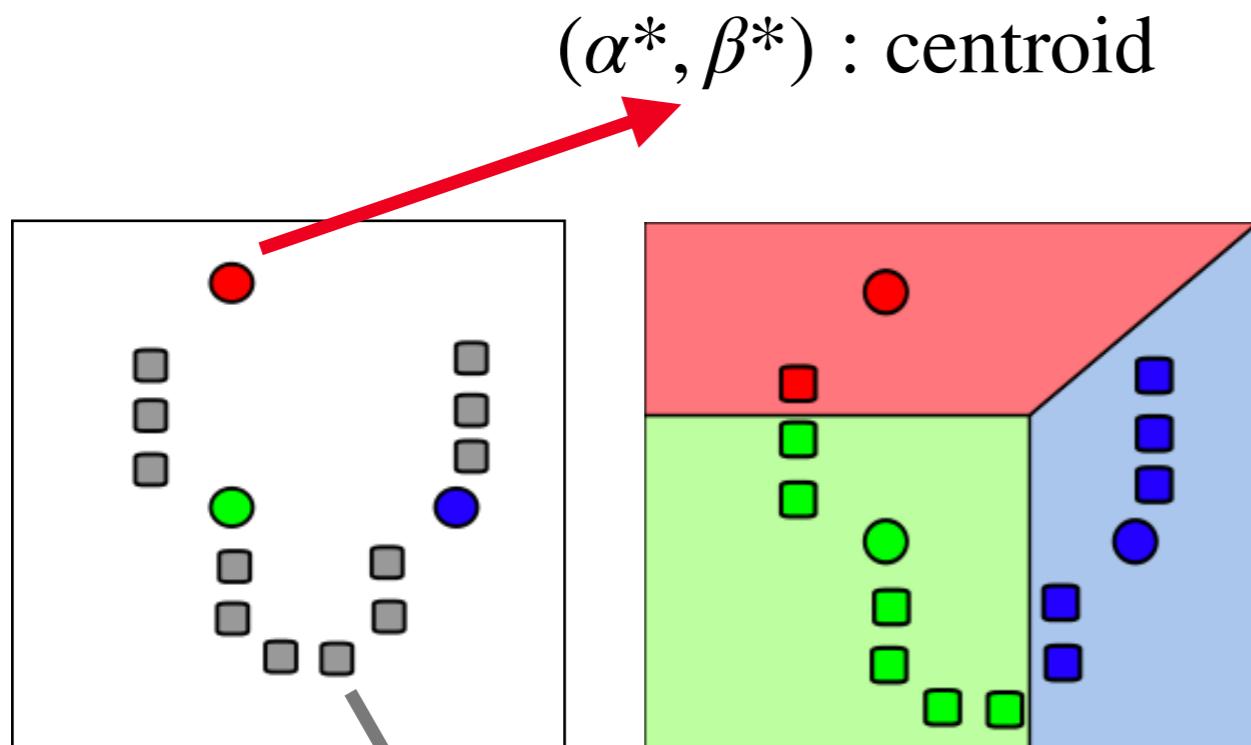
k-means clustering

E.g. $f(x) = x^\alpha (1 - x)^\beta$



k-means clustering

E.g. $f(x) = x^\alpha (1 - x)^\beta$

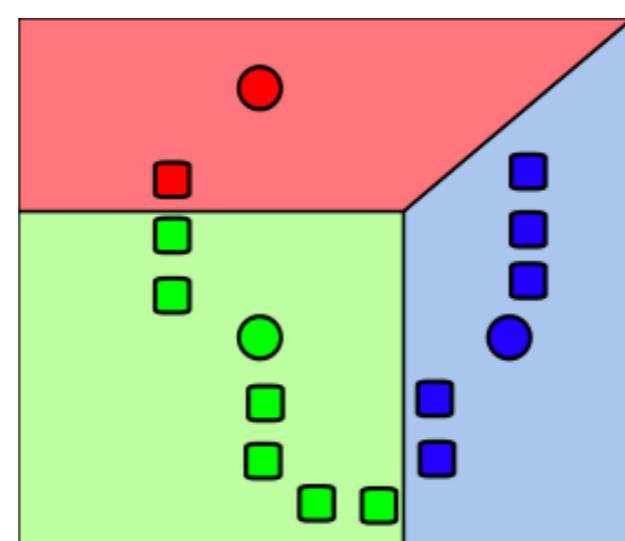


Initialization

Assignment

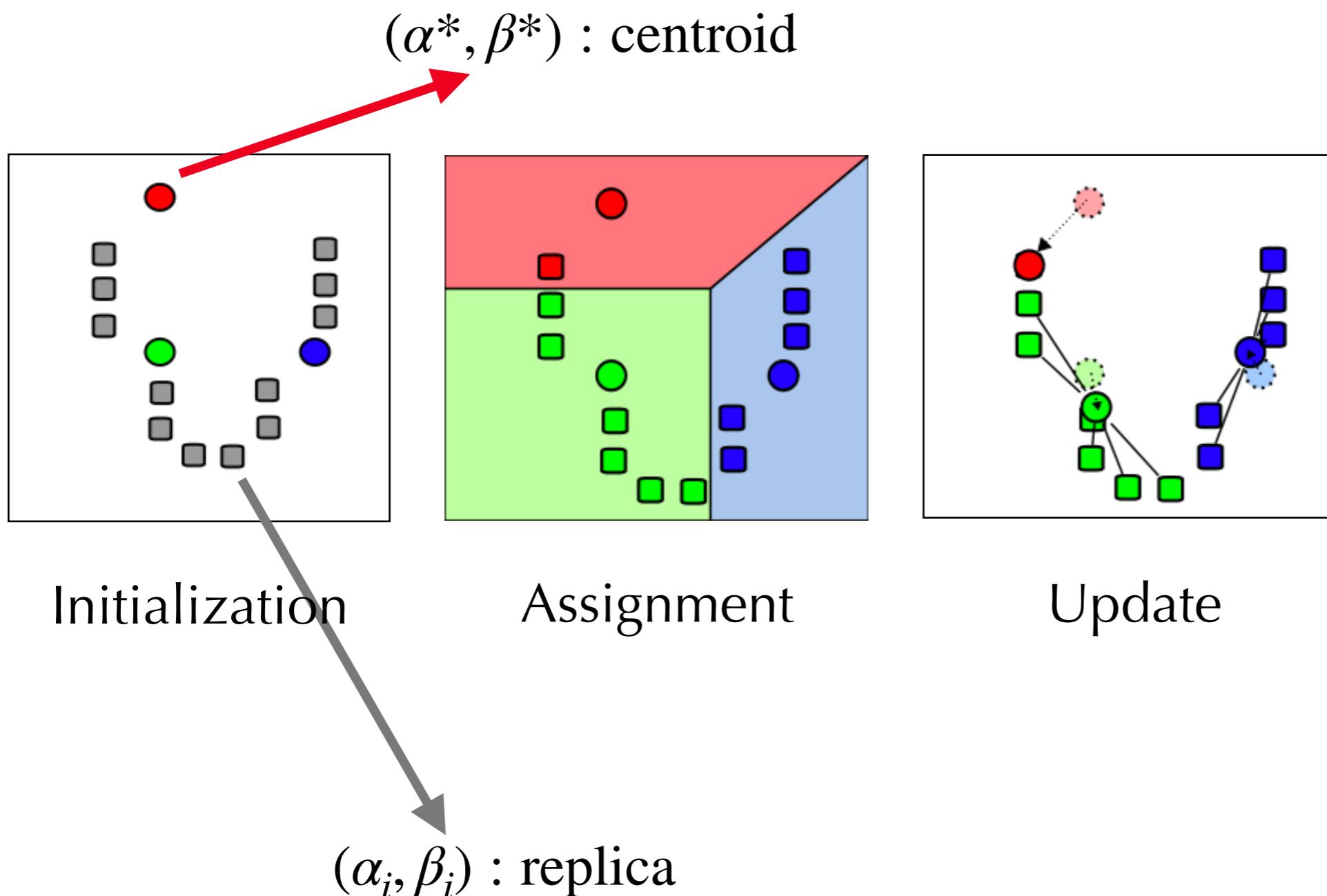
(α_i, β_i) : replica

(α^*, β^*) : centroid



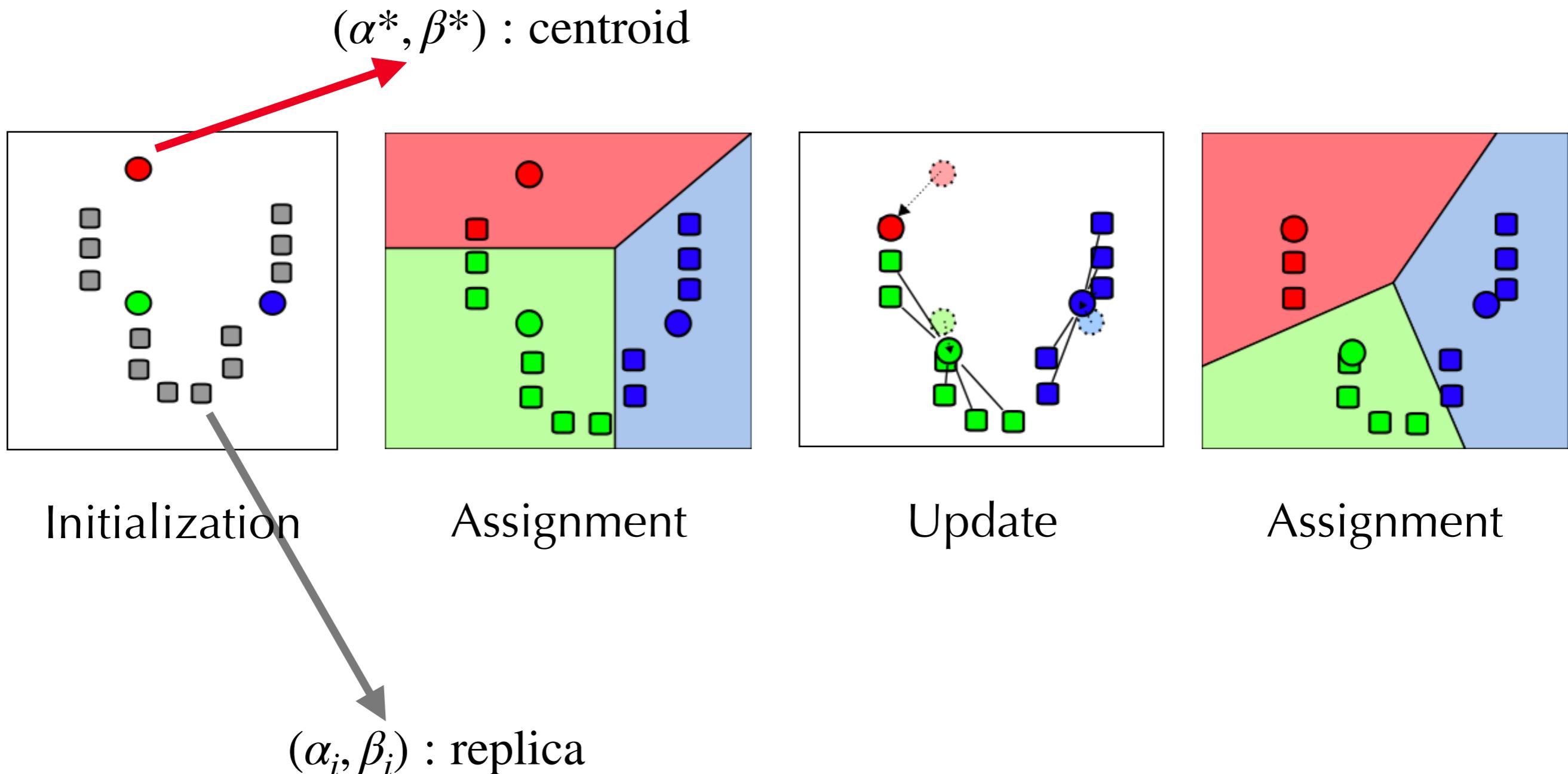
k-means clustering

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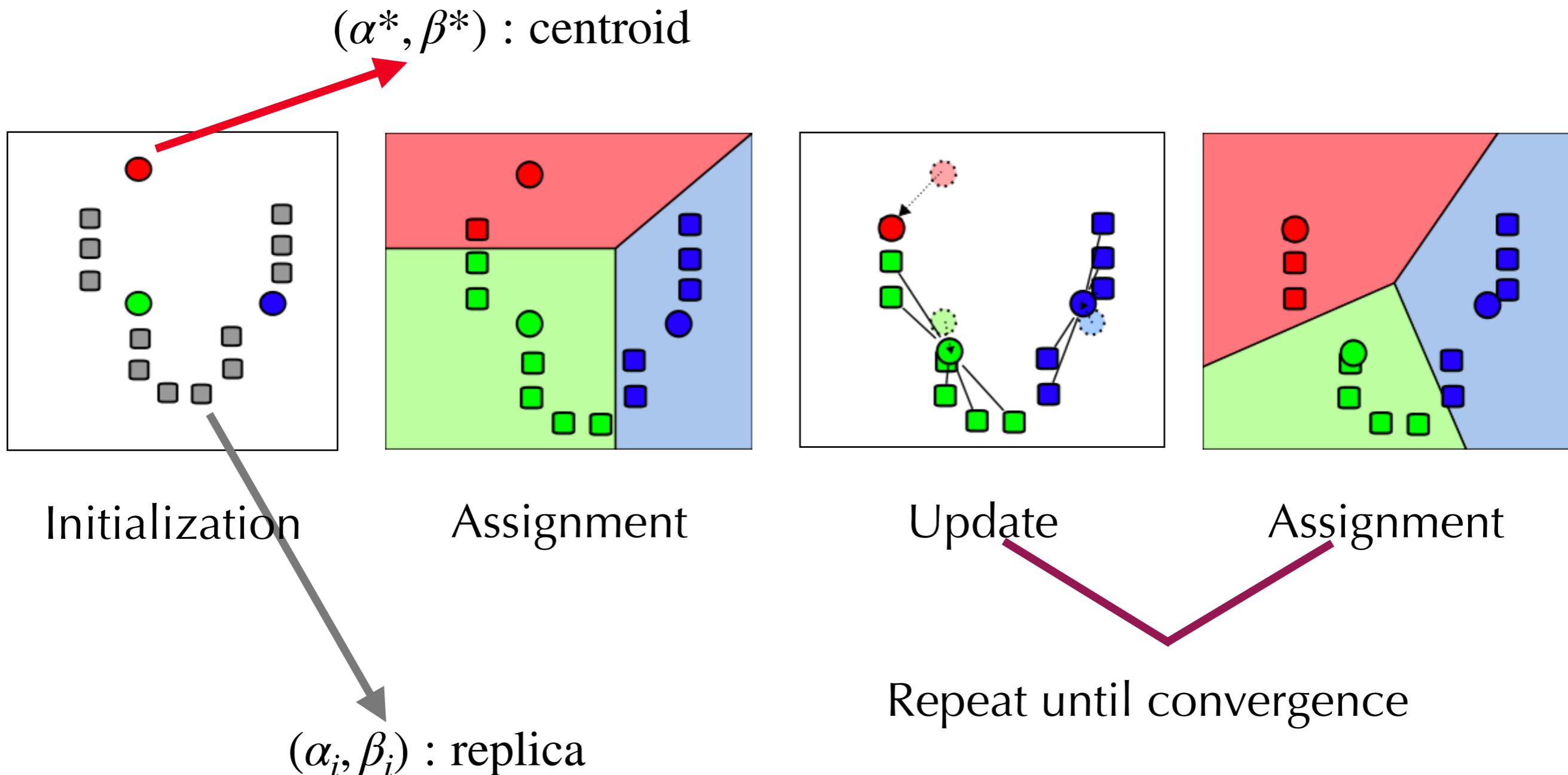
k-means clustering

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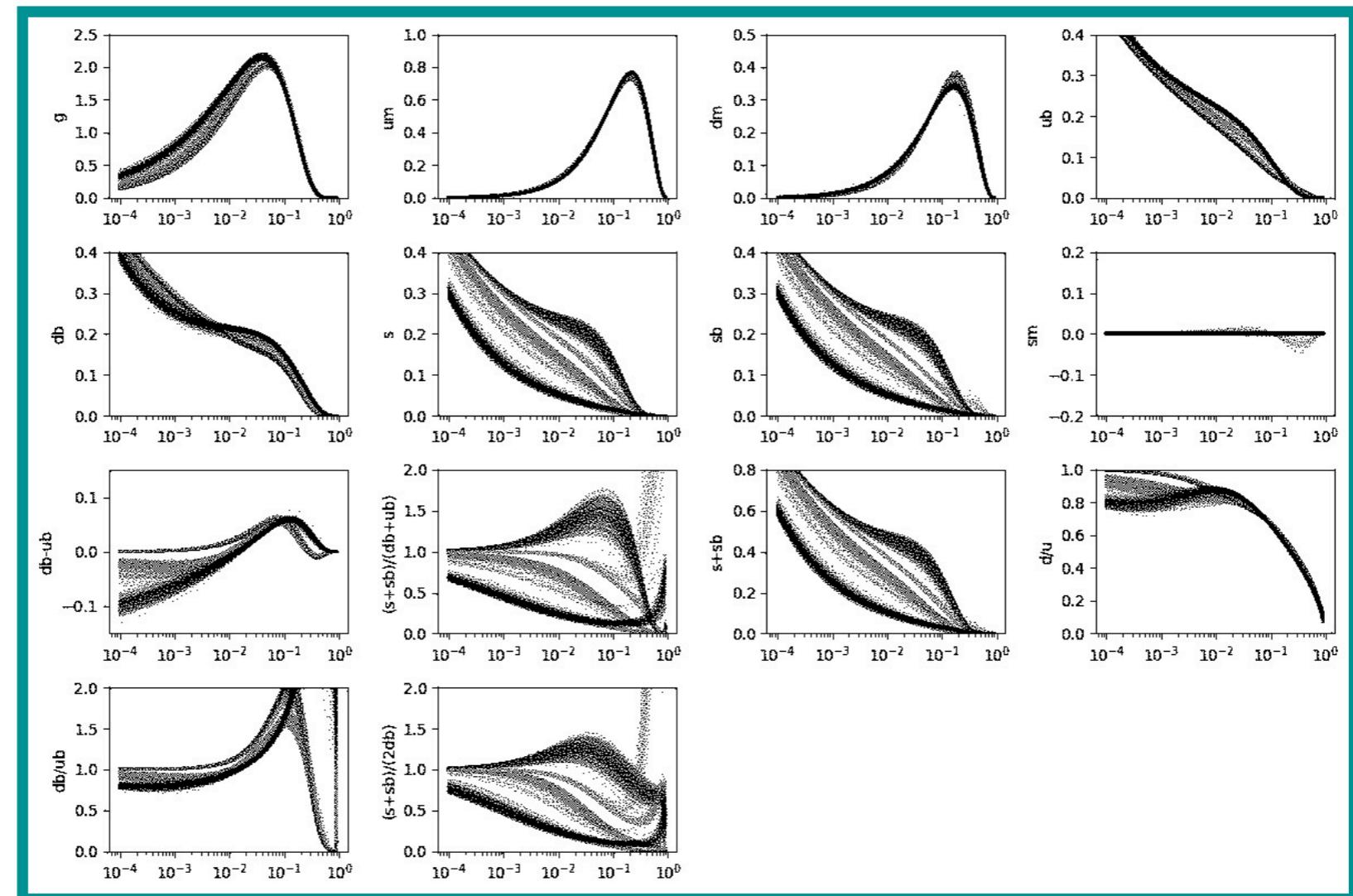
k-means clustering

E.g. $f(x) = x^\alpha (1 - x)^\beta$



Discriminating multiple solutions

+ DIS data

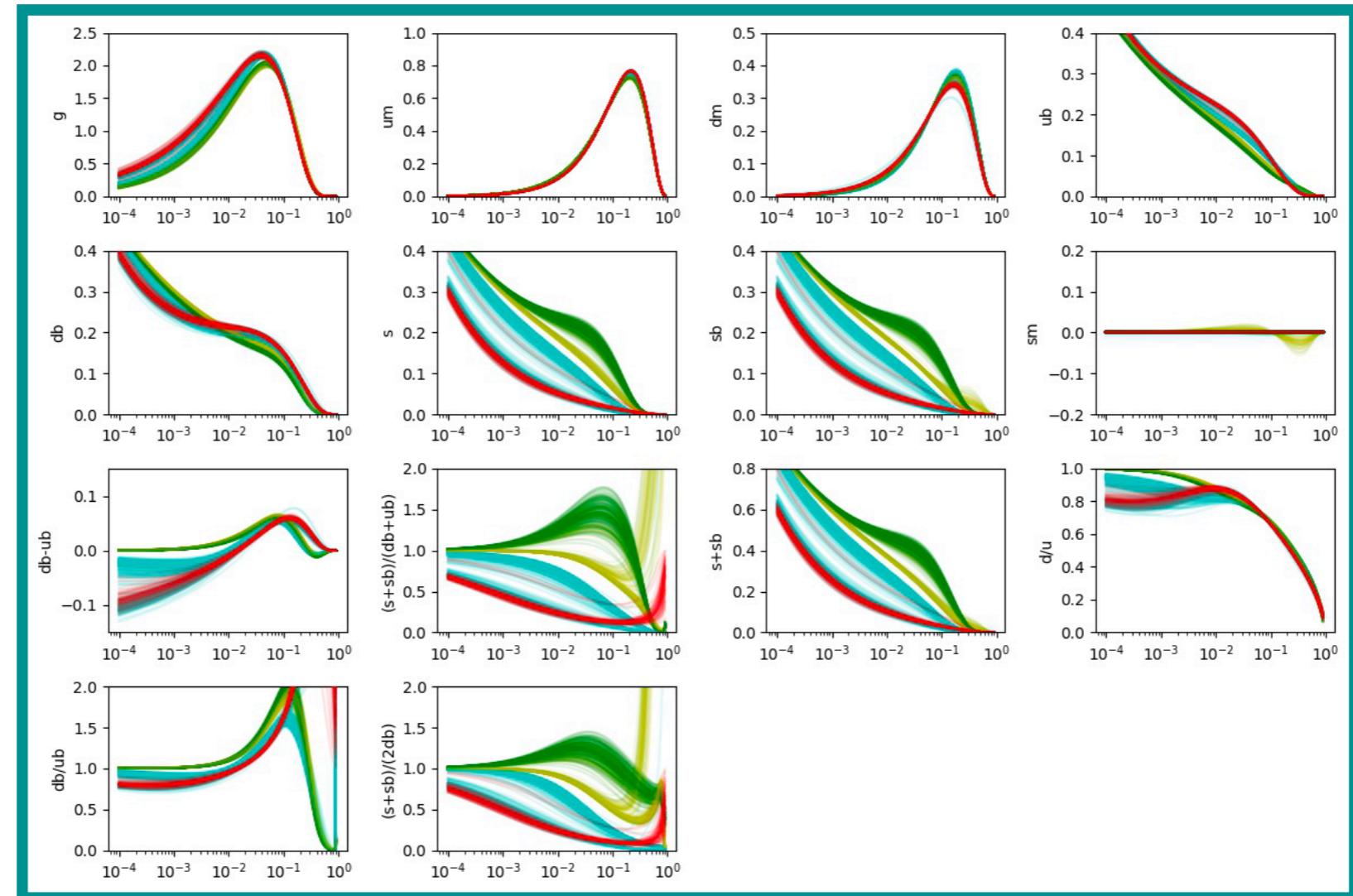


+ DIS + DY data

+ SIDIS data

Discriminating multiple solutions

+ DIS data

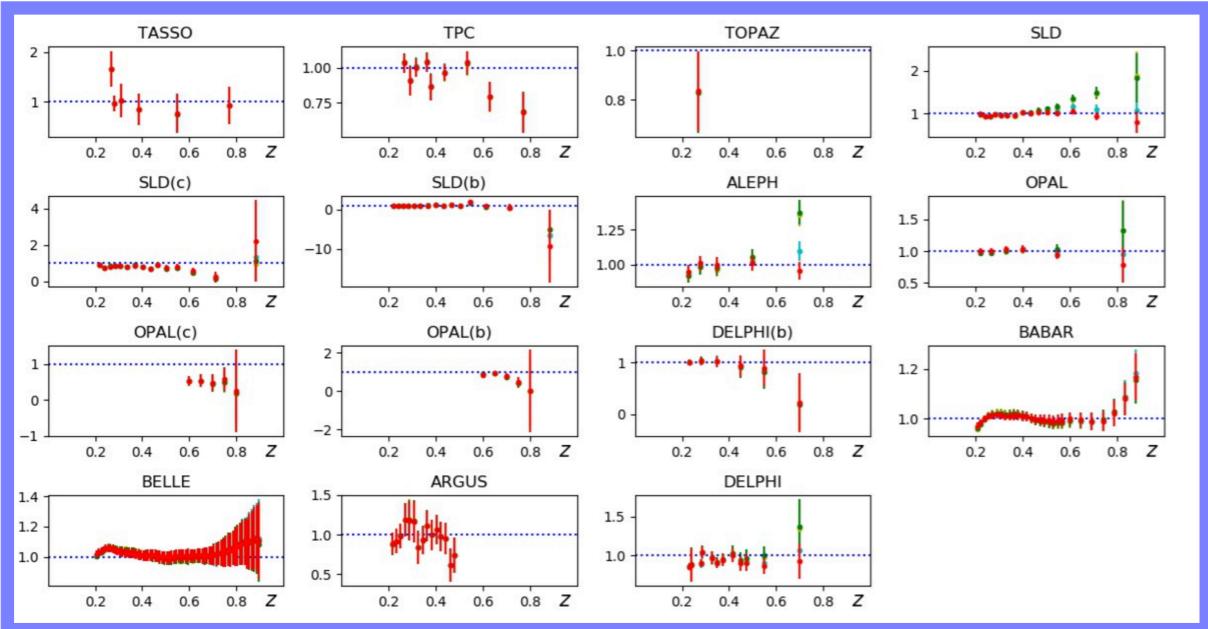


+ DIS + DY data

+ SIDIS data

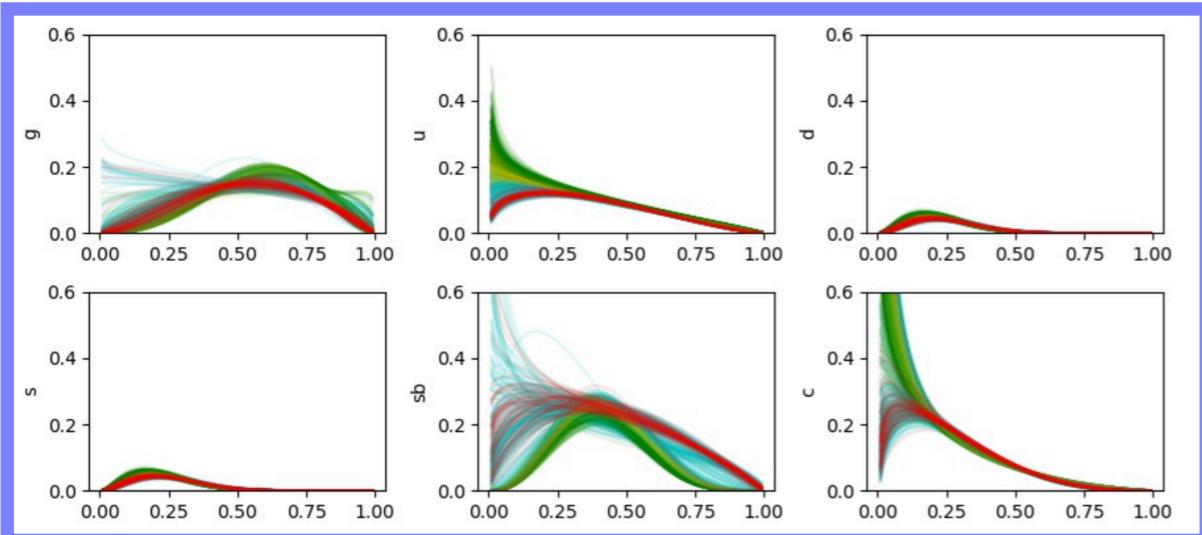
SIA K^+/K^- data

Data/Theory



Z

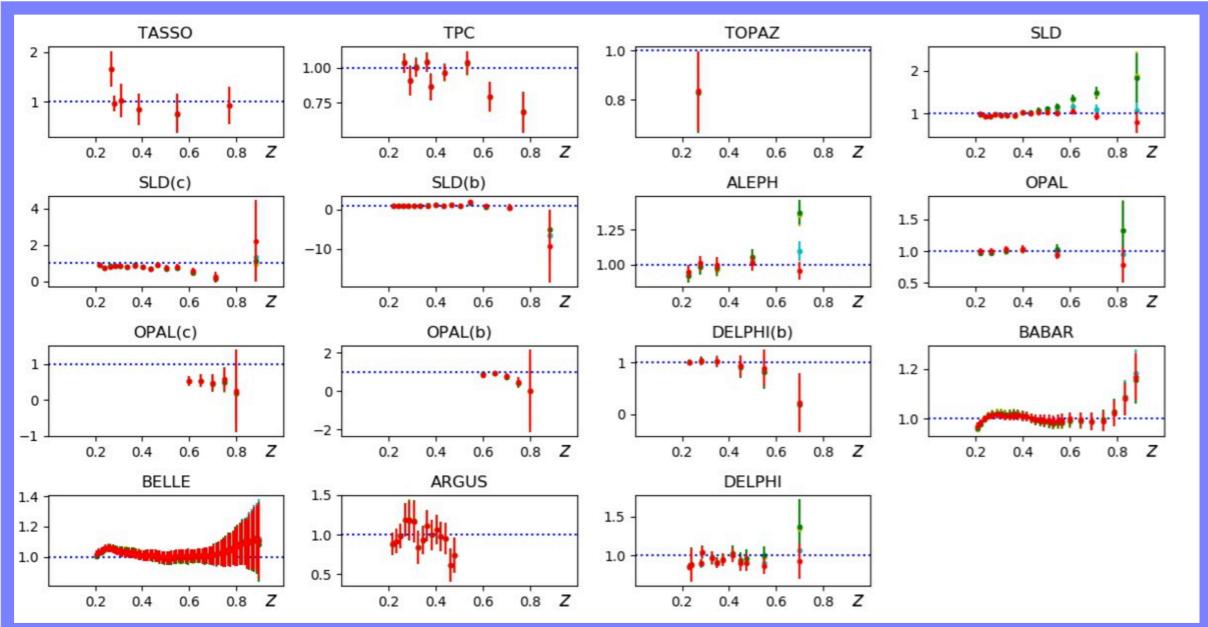
$zD_q^{K^+}$



Z

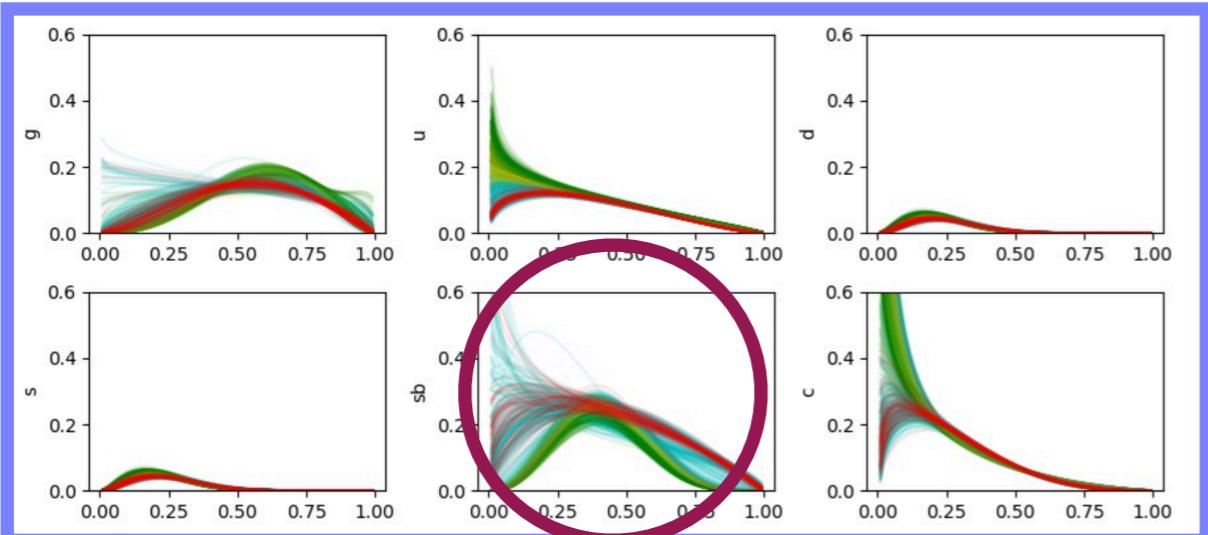
SIA K^+/K^- data

Data/Theory



Z

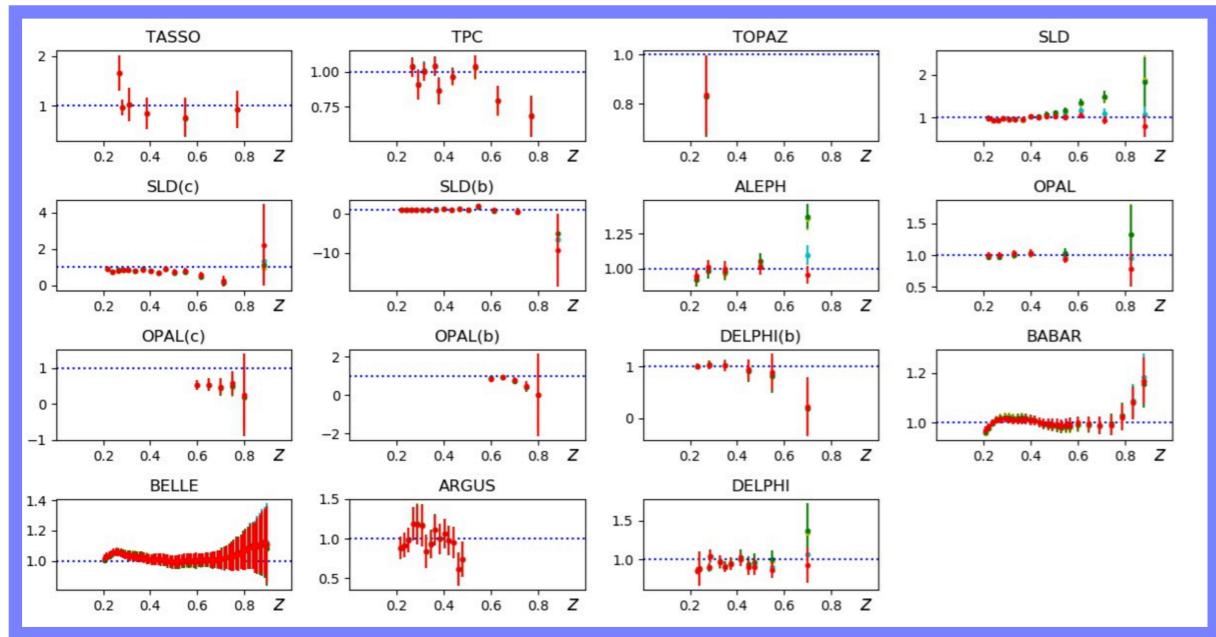
$zD_q^{K^+}$



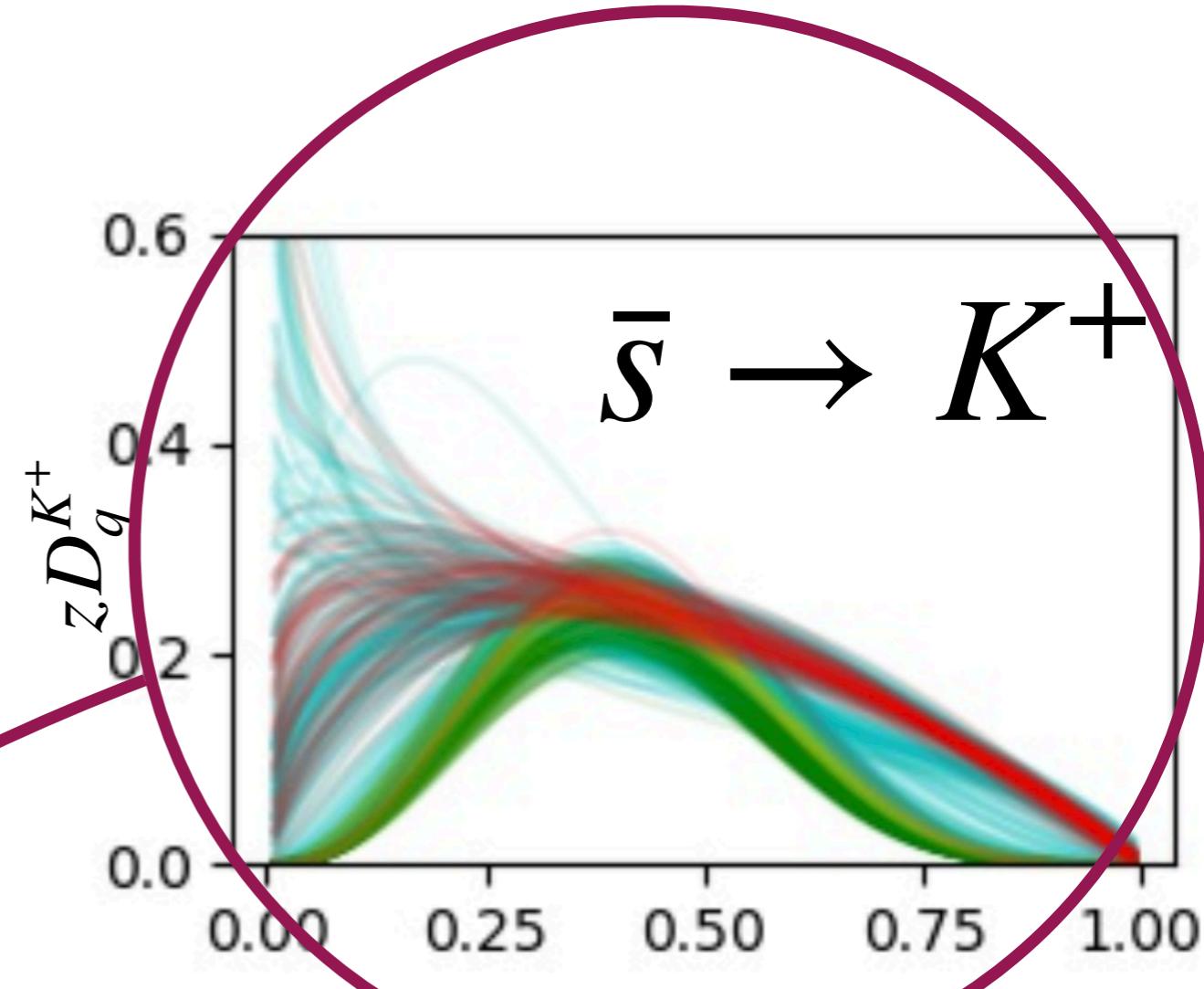
Z

SIA K^+/K^- data

Data/Theory



Z



$zD_q^{K^+}$

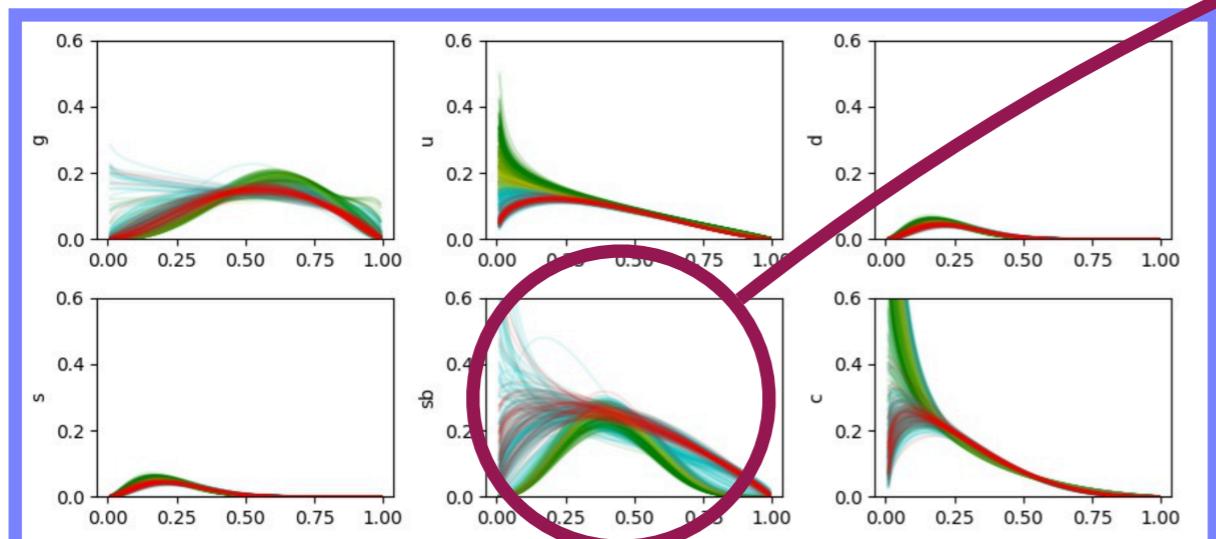
0.6

0.4

0.2

0.0

K^+



Z

SIDIS K-

SIA

Unfavored solutions

Large $s(x)$

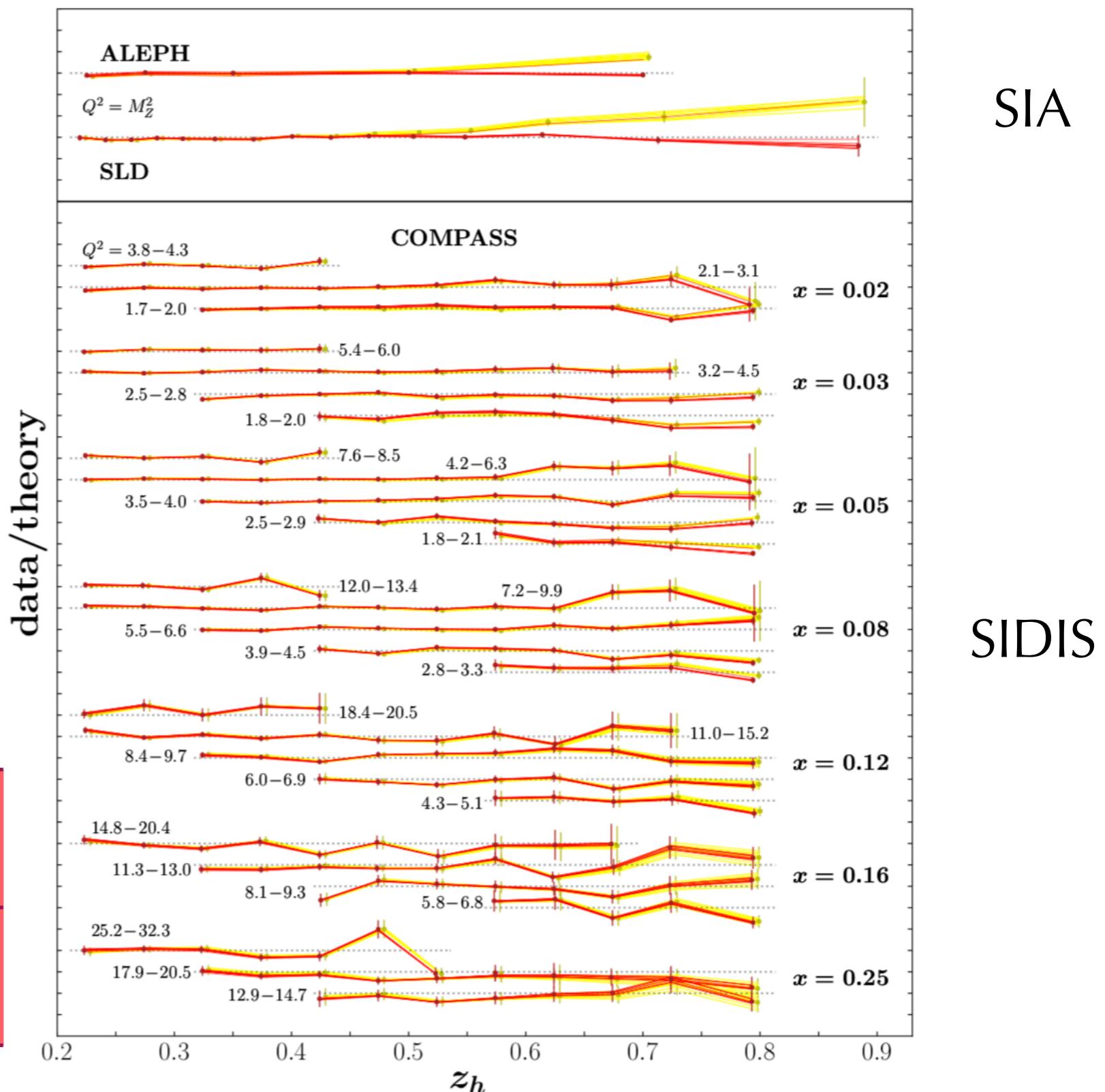
Small $D_{s^\pm}^{K^\pm}(z)$

Favored solutions

Large $D_{s^\pm}^{K^\pm}(z)$

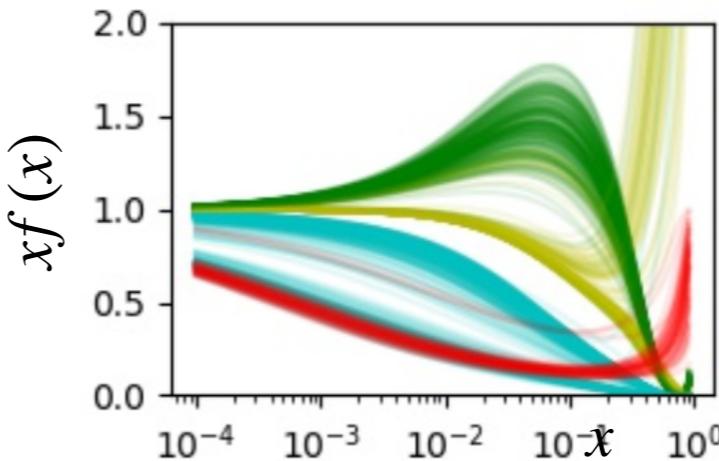
Small $s(x)$

$\chi^2_{\text{SLD}} = 4.10$	$\chi^2_{\text{SLD}} = 1.38$
<hr/>	
$\chi^2_{\text{ALEPH}} = 4.62$	$\chi^2_{\text{ALEPH}} = 0.34$



JAM19: Selection criteria

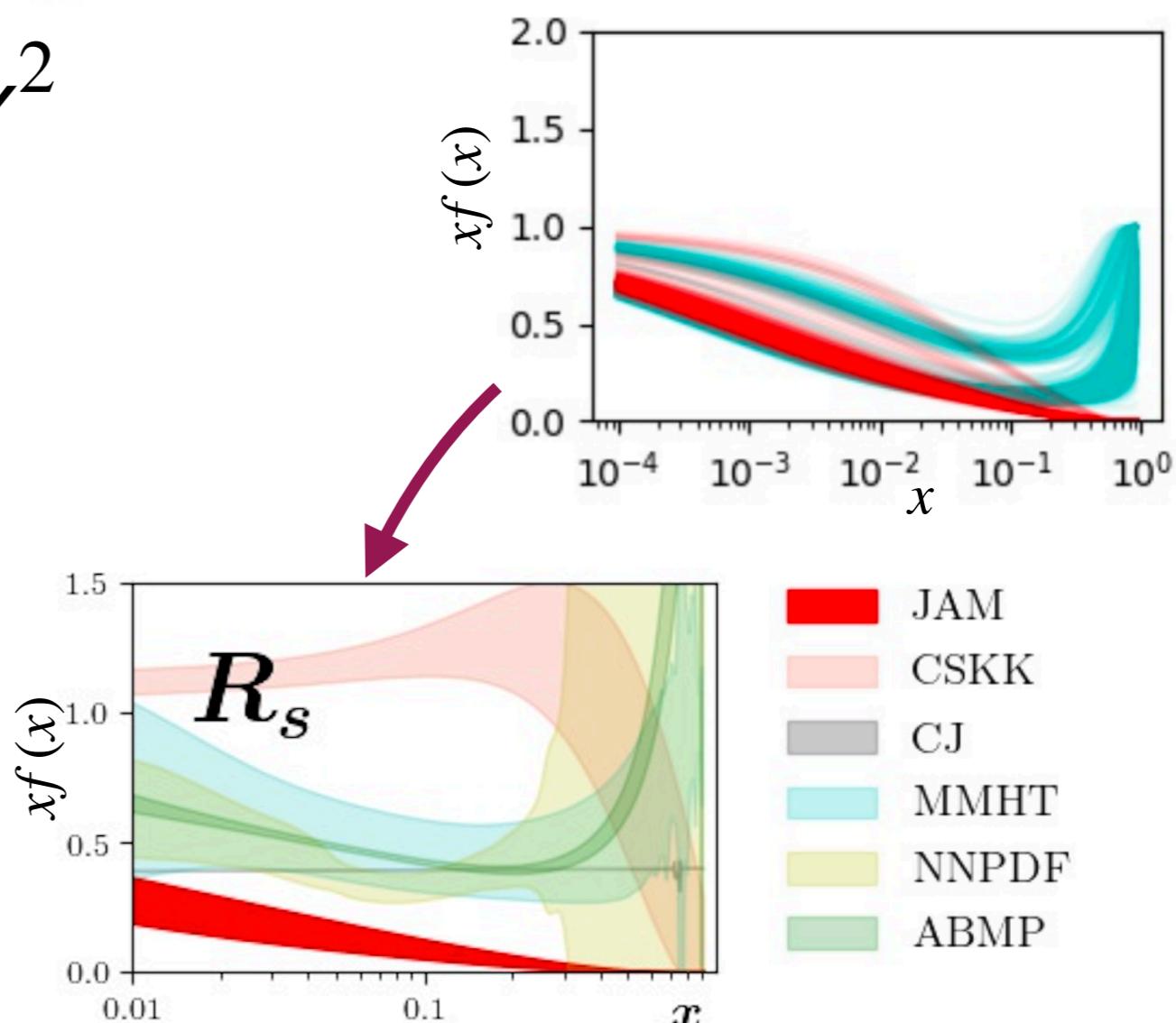
- Apply k-means clustering



- Classify clusters by increasing χ^2 order in 'extended' reduced

$$\frac{\chi^2}{N_{\text{tot}}} + \sum_{\text{exp}} \frac{\chi^2_{\text{exp}}}{N_{\text{exp}}}$$

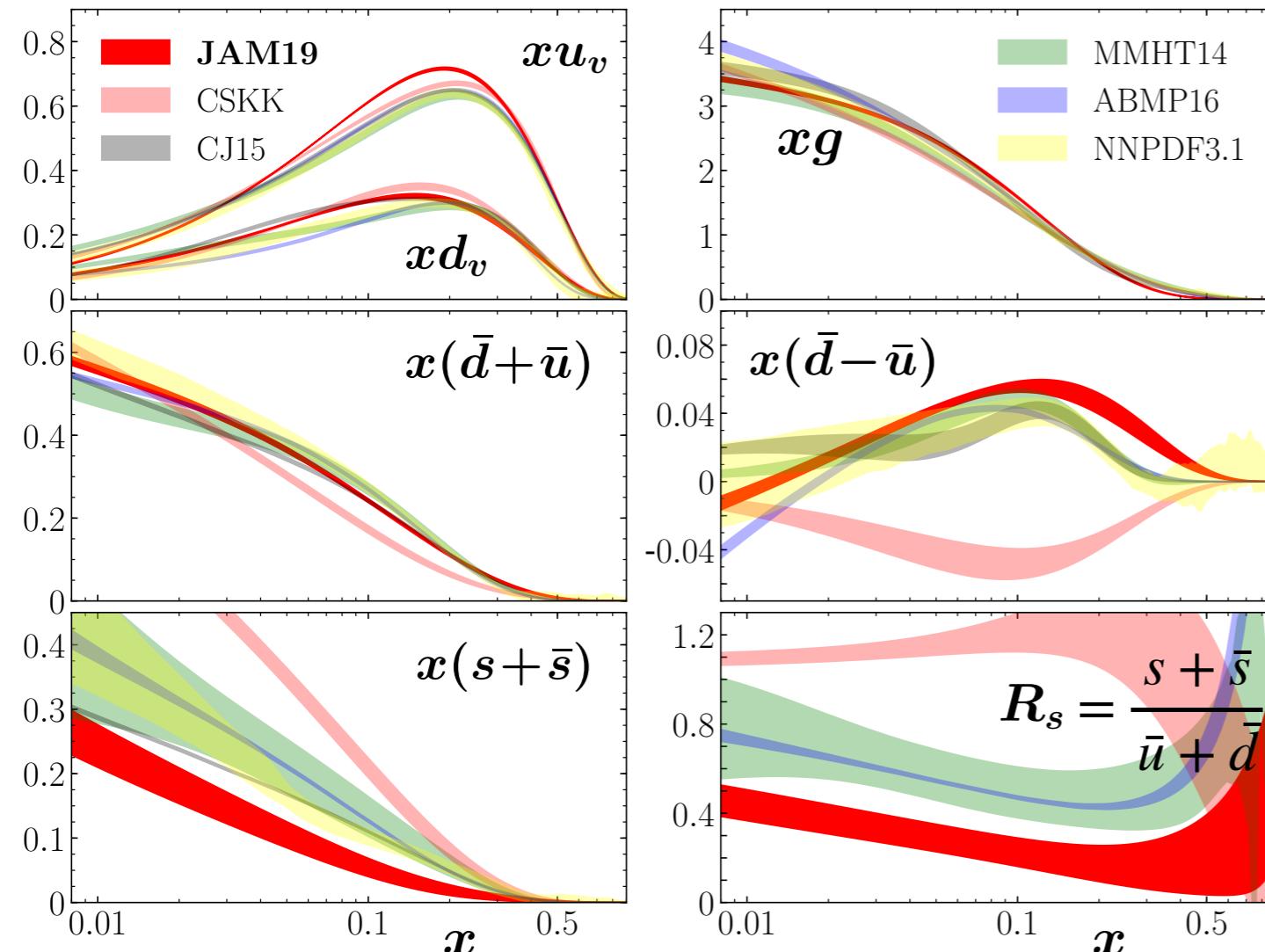
- Perform a new sampling with flat priors around the best cluster



PDF results

JAM19 PDFs

arXiv:1905.03788 [hep-ph]

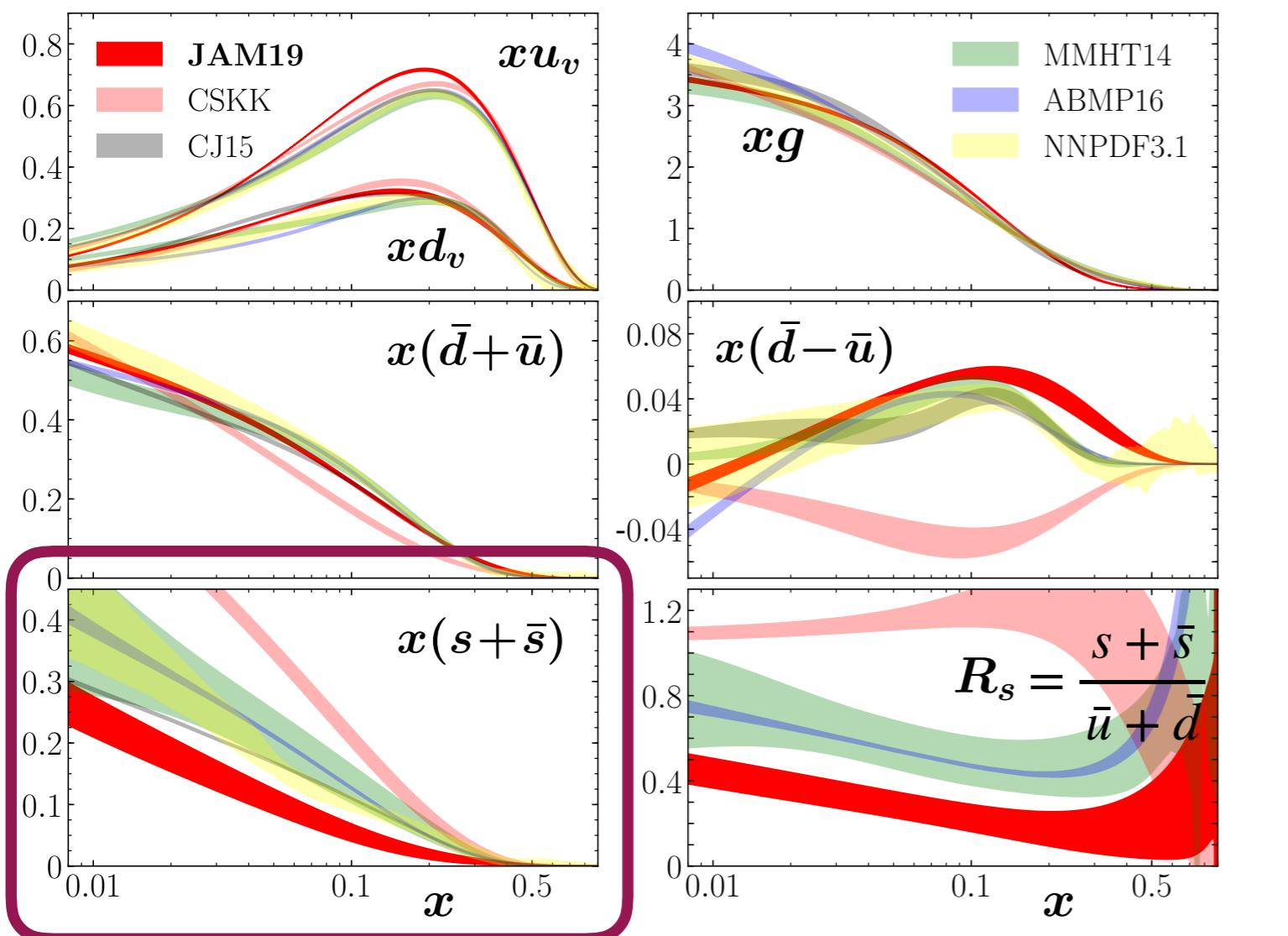


$Q = 2 \text{ GeV}$

$\text{DIS}(p, d)$
 $\text{DY}(pp, pd)$
 $\text{SIA}(\pi^\pm, K^\pm)$
 $\text{SIDIS}(\pi^\pm, K^\pm)$

JAM19 PDFs

arXiv:1905.03788 [hep-ph]

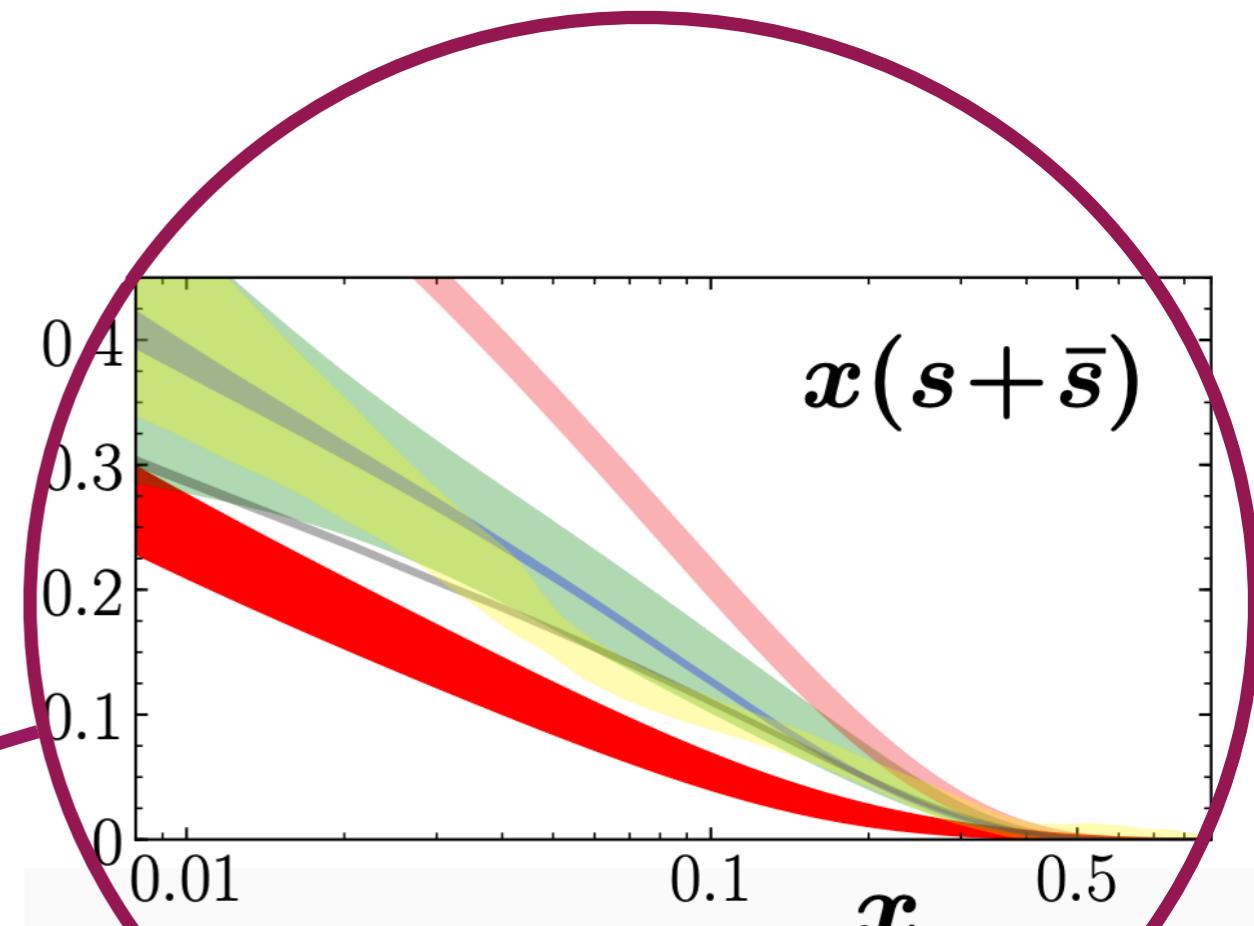
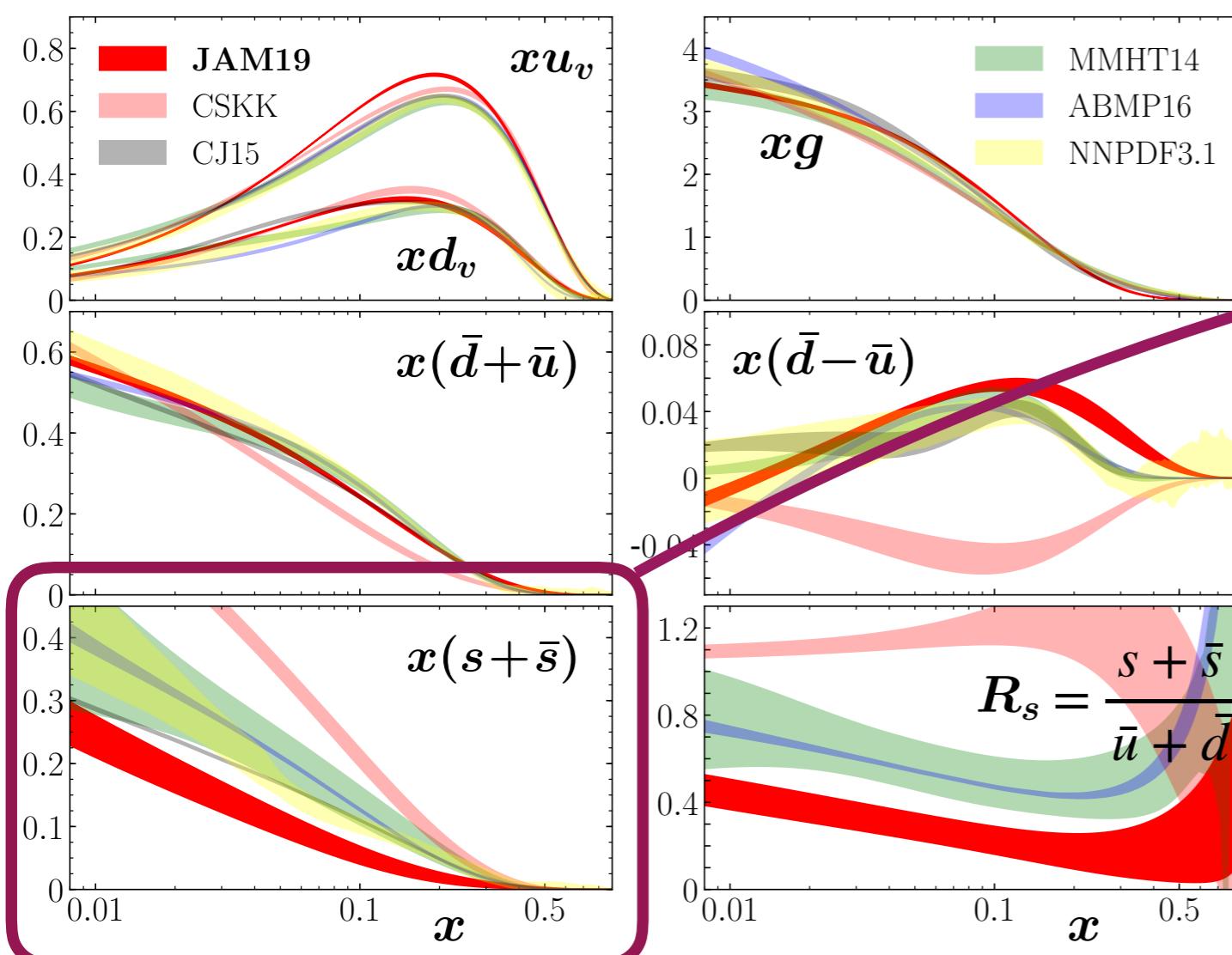


$Q = 2 \text{ GeV}$

$\text{DIS}(p, d)$
 $\text{DY}(pp, pd)$
 $\text{SIA}(\pi^\pm, K^\pm)$
 $\text{SIDIS}(\pi^\pm, K^\pm)$

JAM19 PDFs

[arXiv:1905.03788 \[hep-ph\]](https://arxiv.org/abs/1905.03788)



Strong strange suppression

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

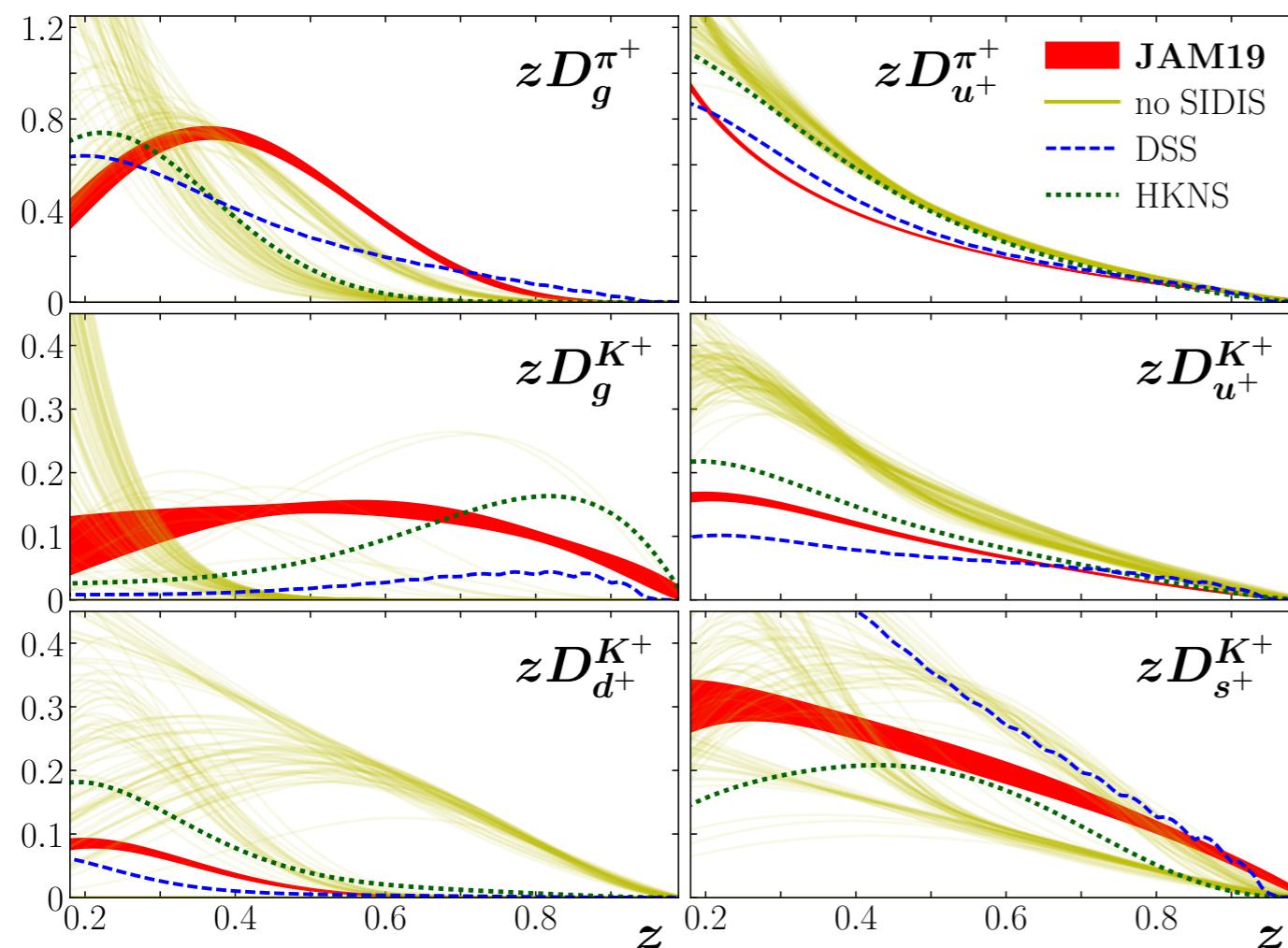
DIS(p, d)
DY(pp, pd)
SIA(π^\pm, K^\pm)
SIDIS(π^\pm, K^\pm)

$Q = 2 \text{ GeV}$

FF results

JAM19: FF

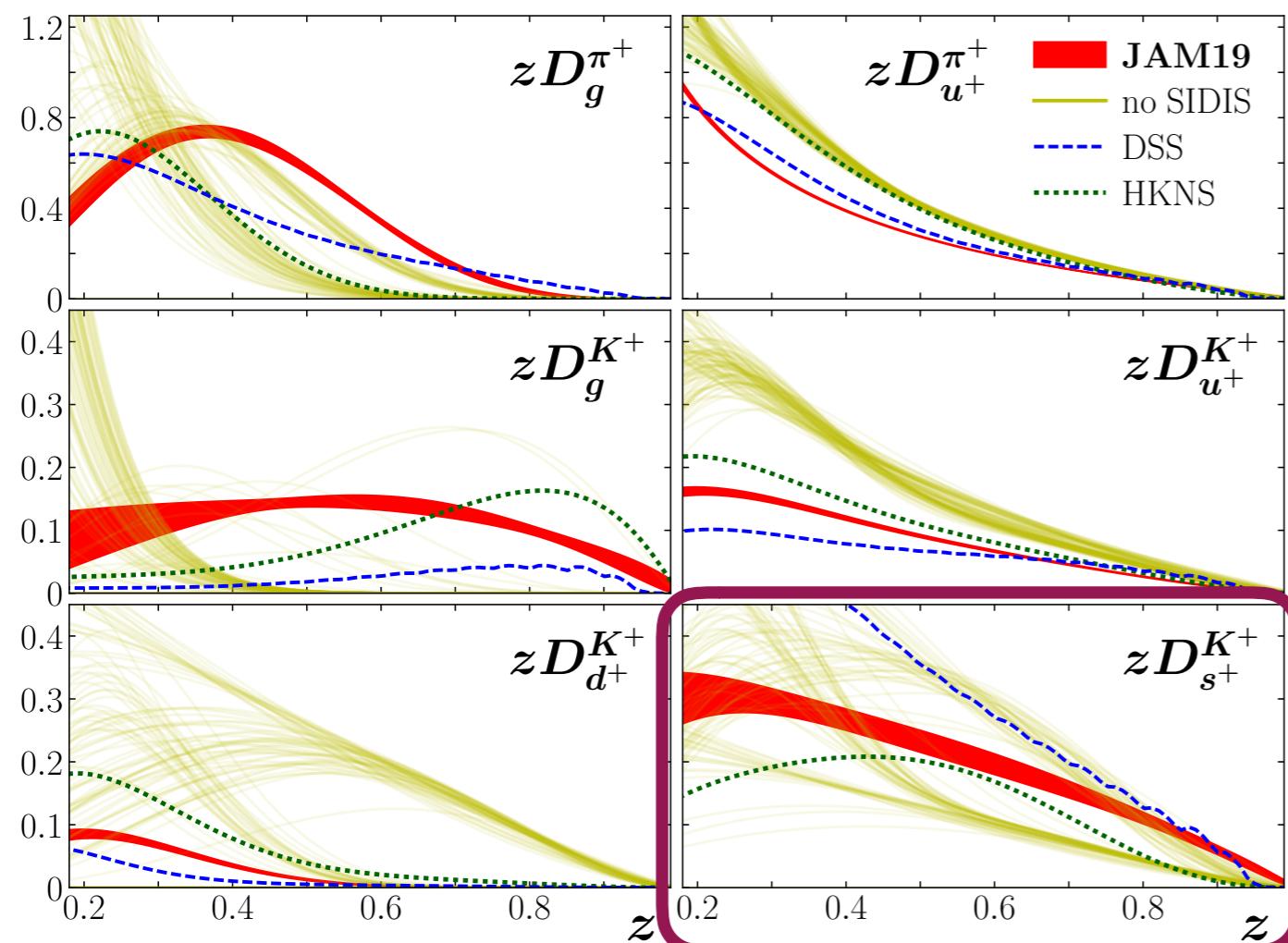
arXiv:1905.03788 [hep-ph]



$$\mathbf{Q} = \mathbf{m}_c$$

JAM19: FF

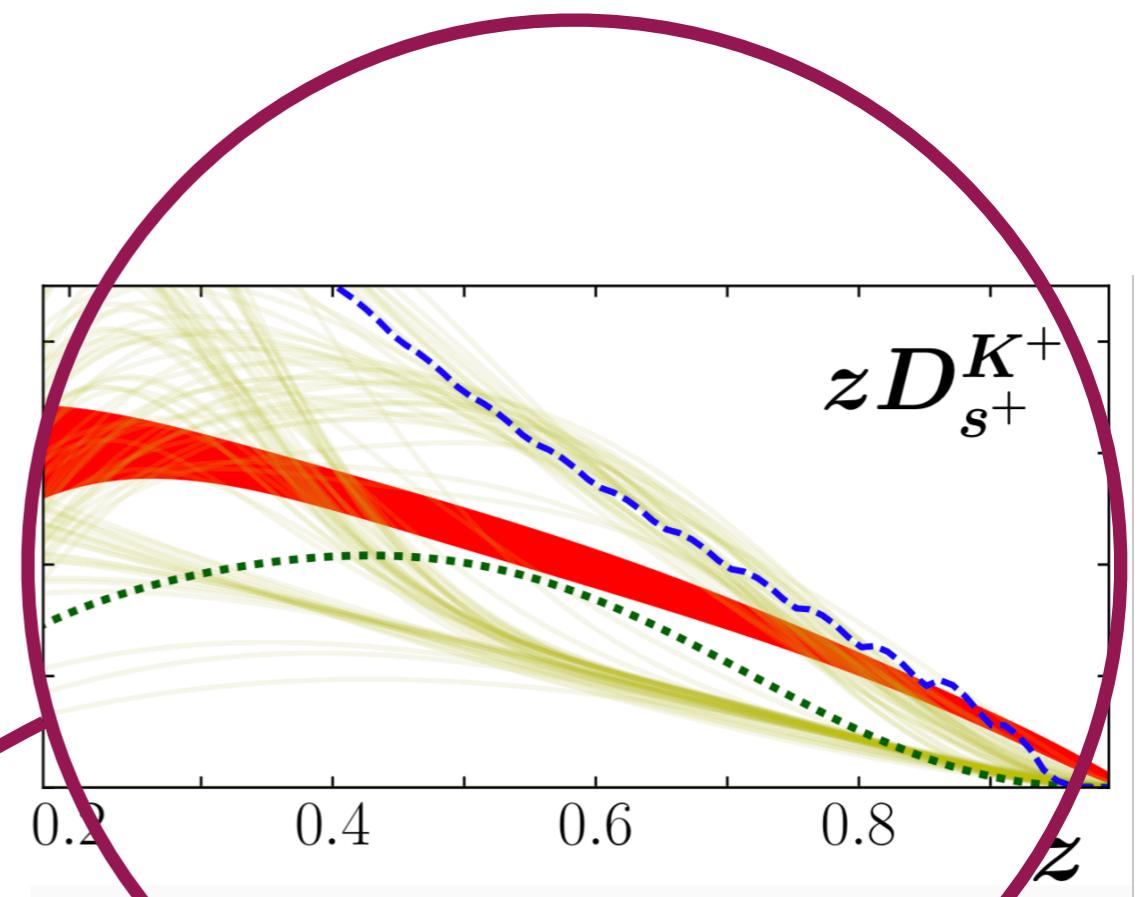
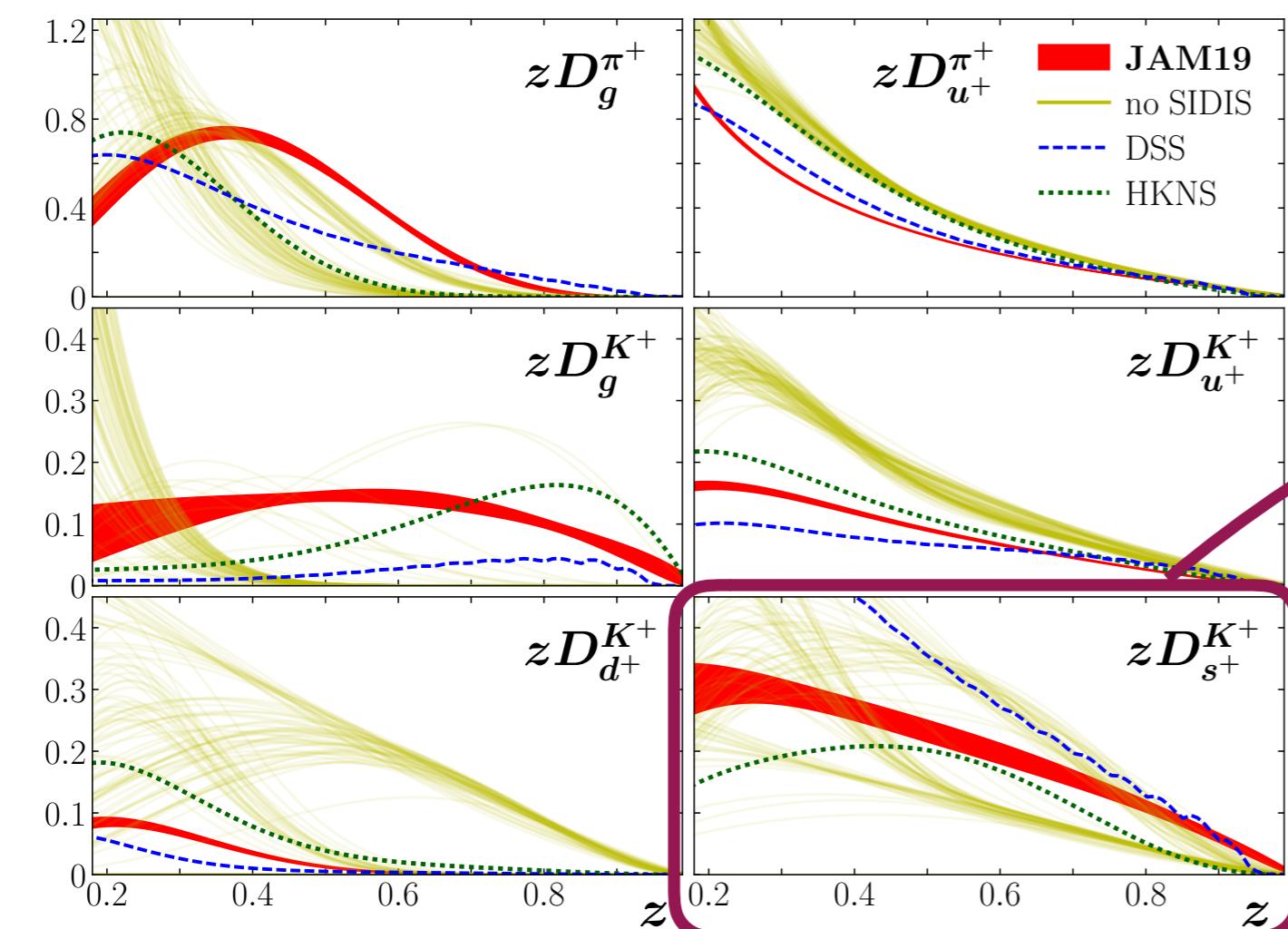
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$$\mathbf{Q} = \mathbf{m}_c$$

JAM19: FF

arXiv:1905.03788 [hep-ph]



Large $\bar{s} \rightarrow K^+$

$$Q = m_c$$

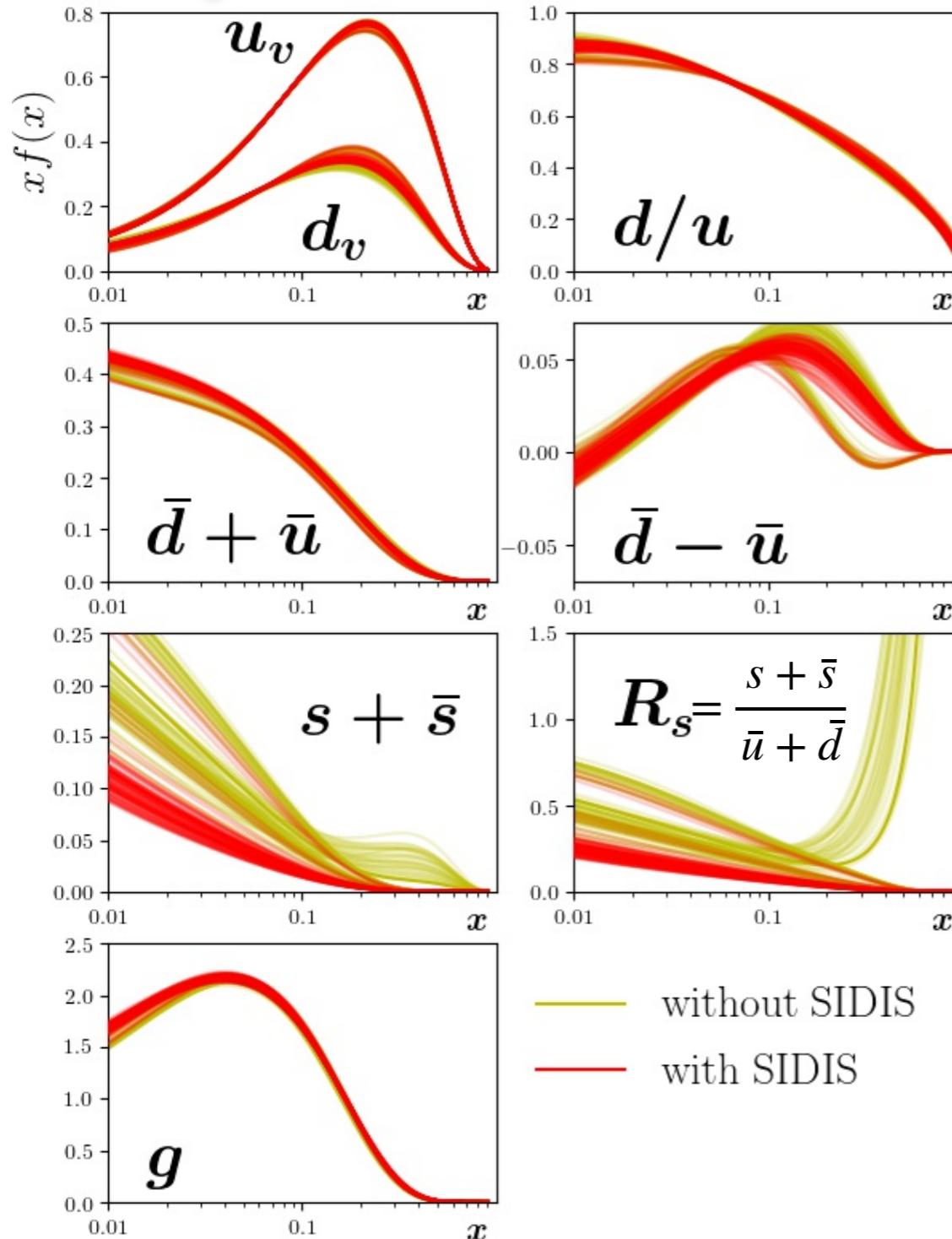
Summary

- **Fitting** several (or all) non-perturbative collinear distributions **simultaneously is very challenging**
- **MC** statistical methods are important for a **robust extraction**
(Crucial for future global TMDs, GPDs analysis)
- **New methodology** needed: MC **multi-steps fit**, k-means clustering, ‘extended’ reduced χ^2
- First simultaneous fit of unpolarized PDFs and FFs: **strange PDF strongly suppressed**

Backup

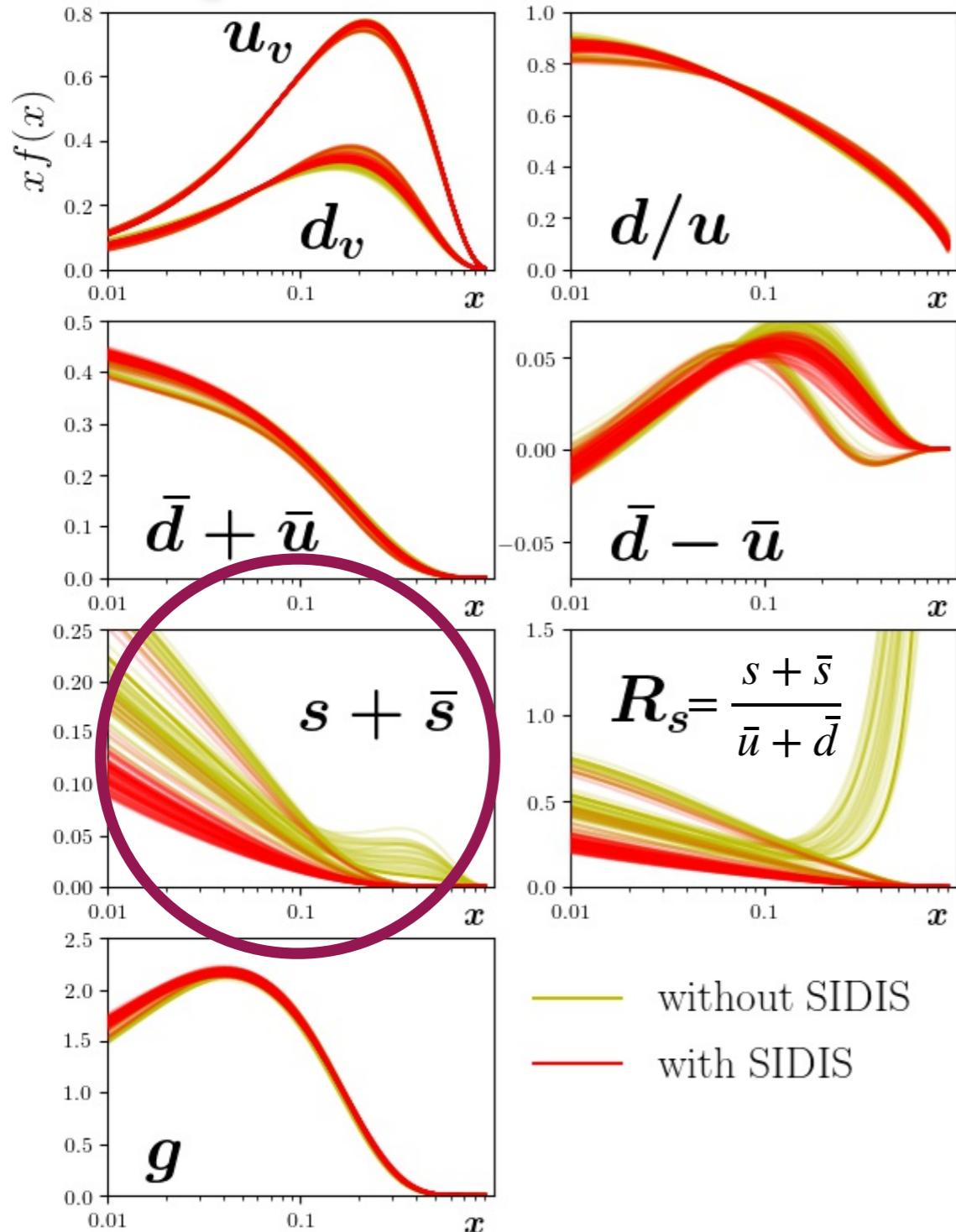
Impact of SIDIS data

Impact of SIDIS data on PDFs



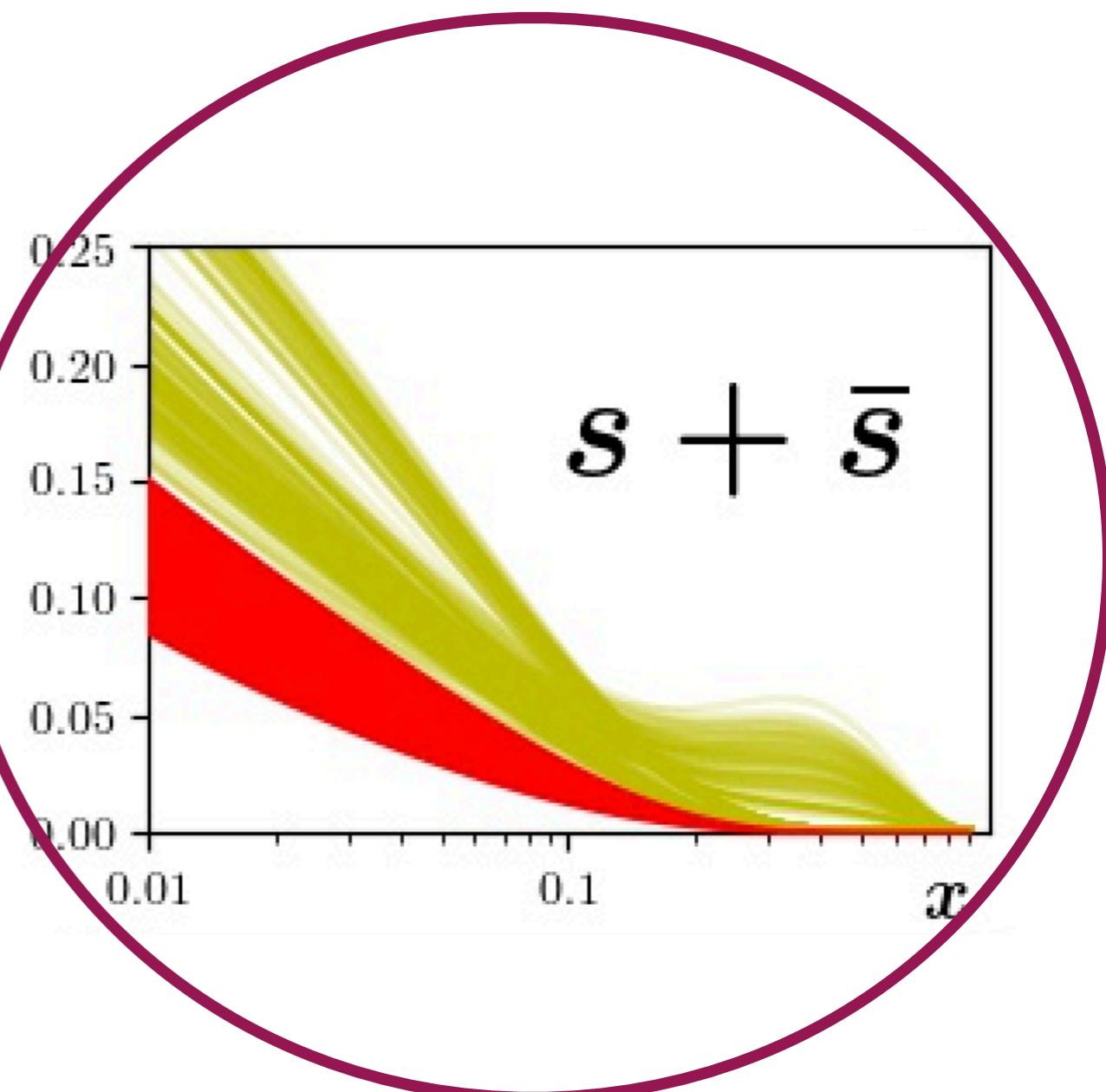
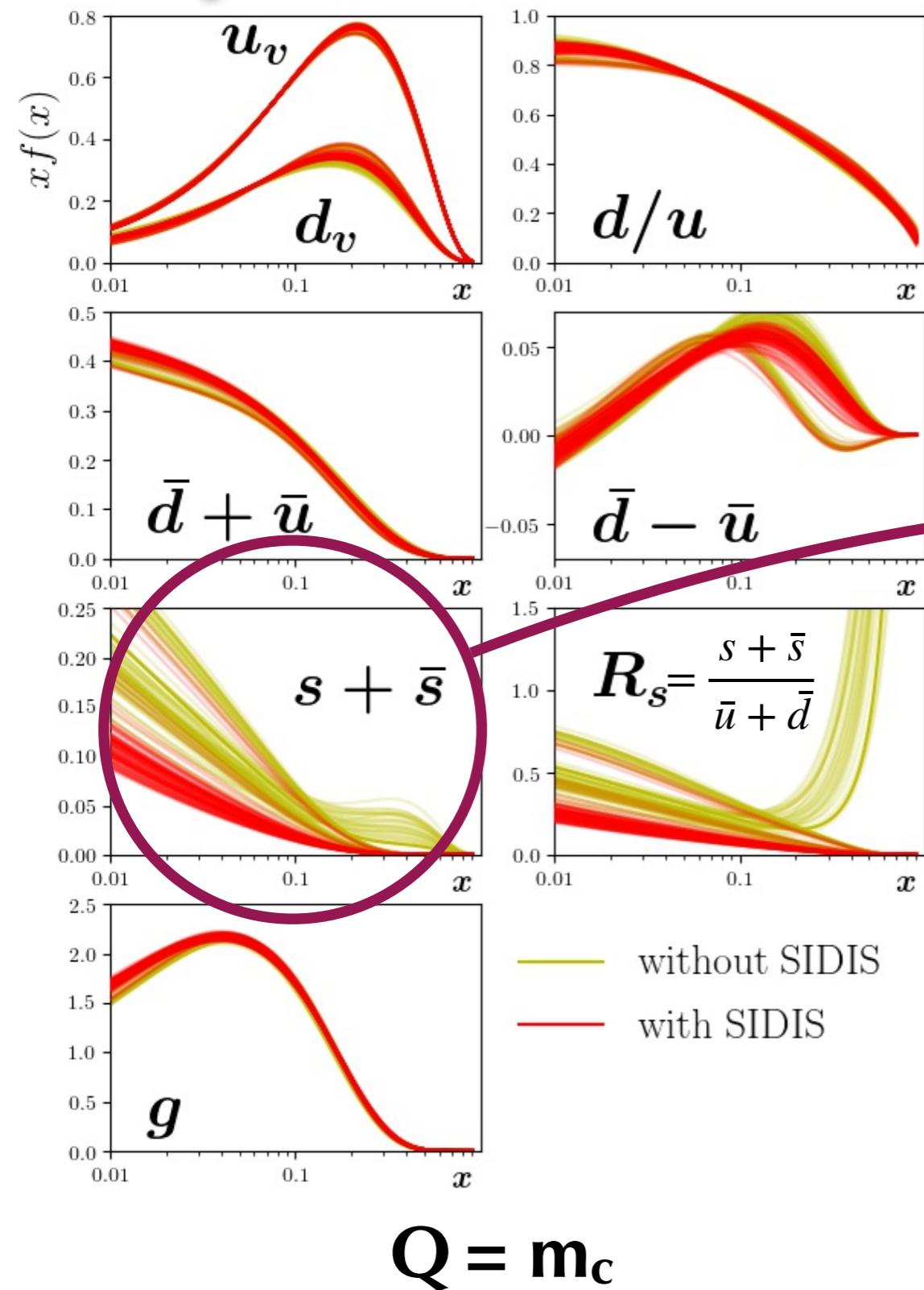
$$Q = m_c$$

Impact of SIDIS data on PDFs



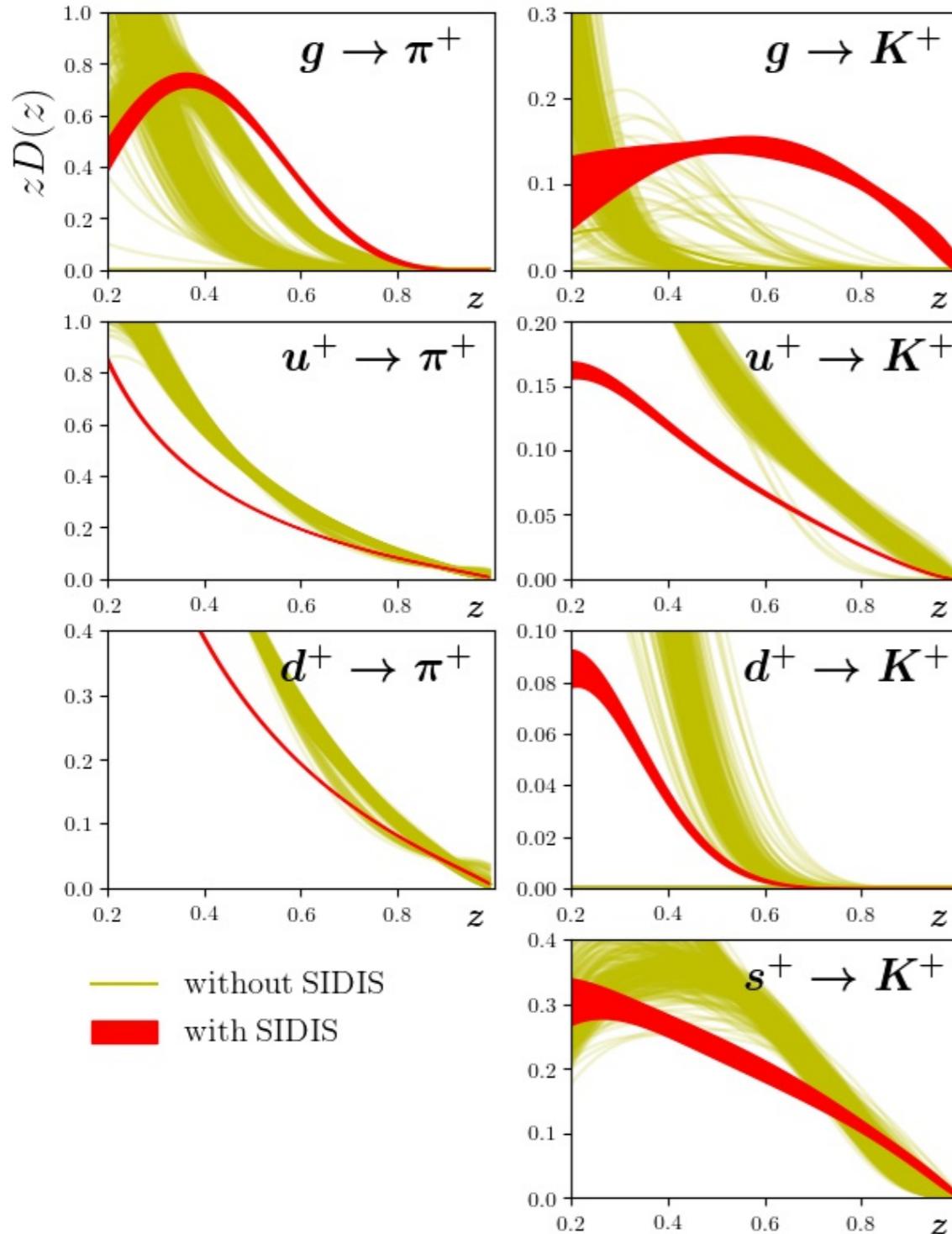
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Impact of SIDIS data on PDFs



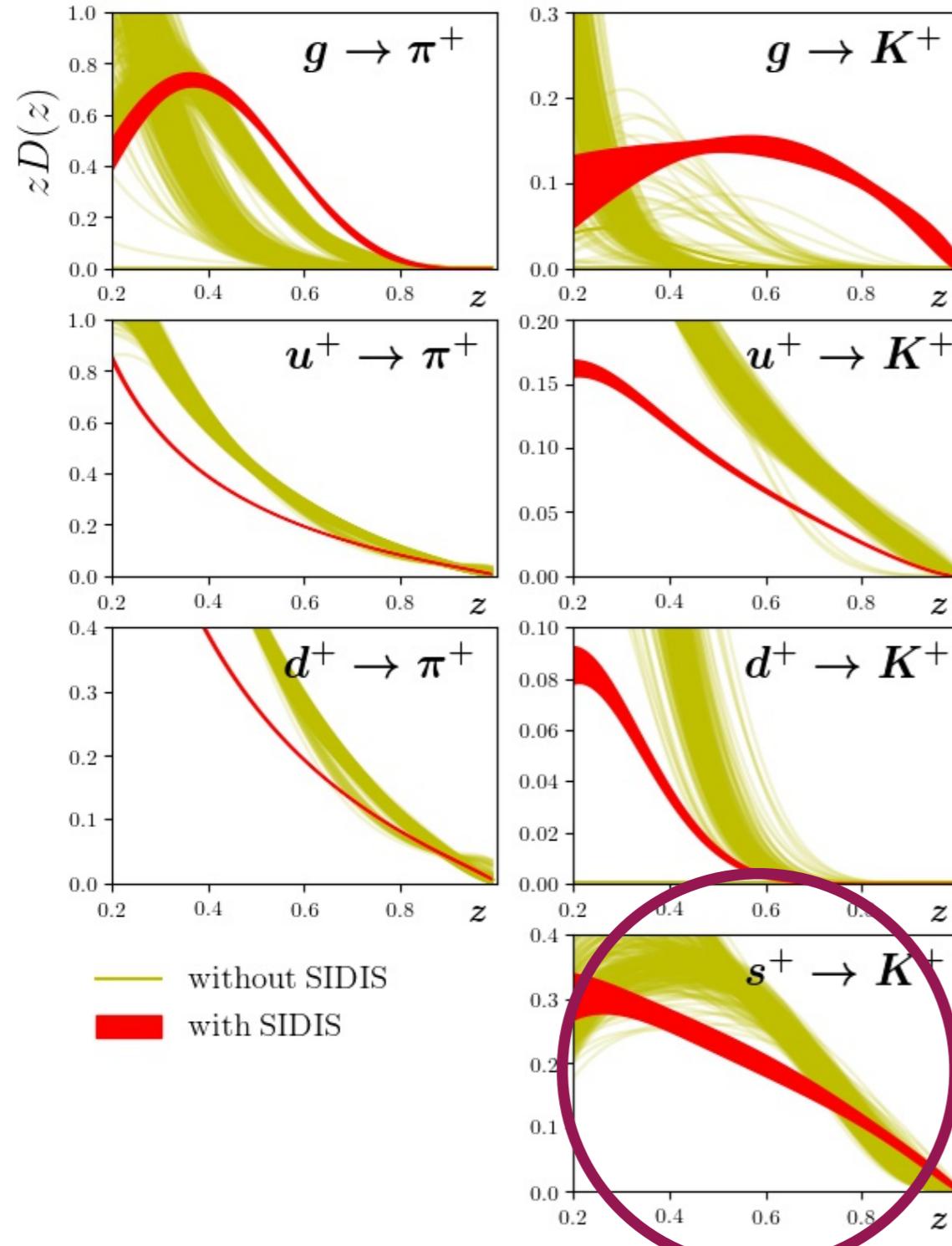
Strong strange
suppression

Impact of SIDIS data on FFs



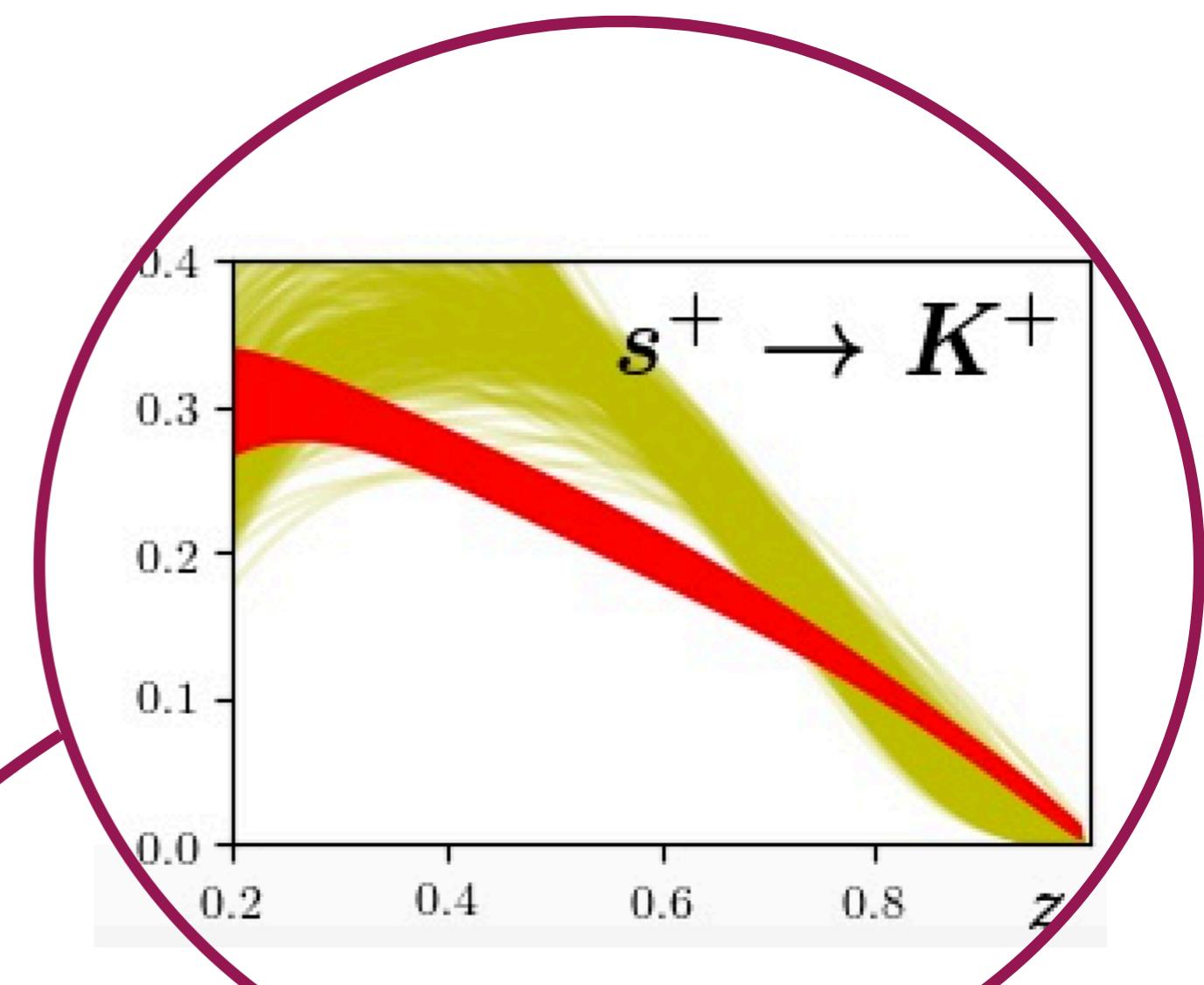
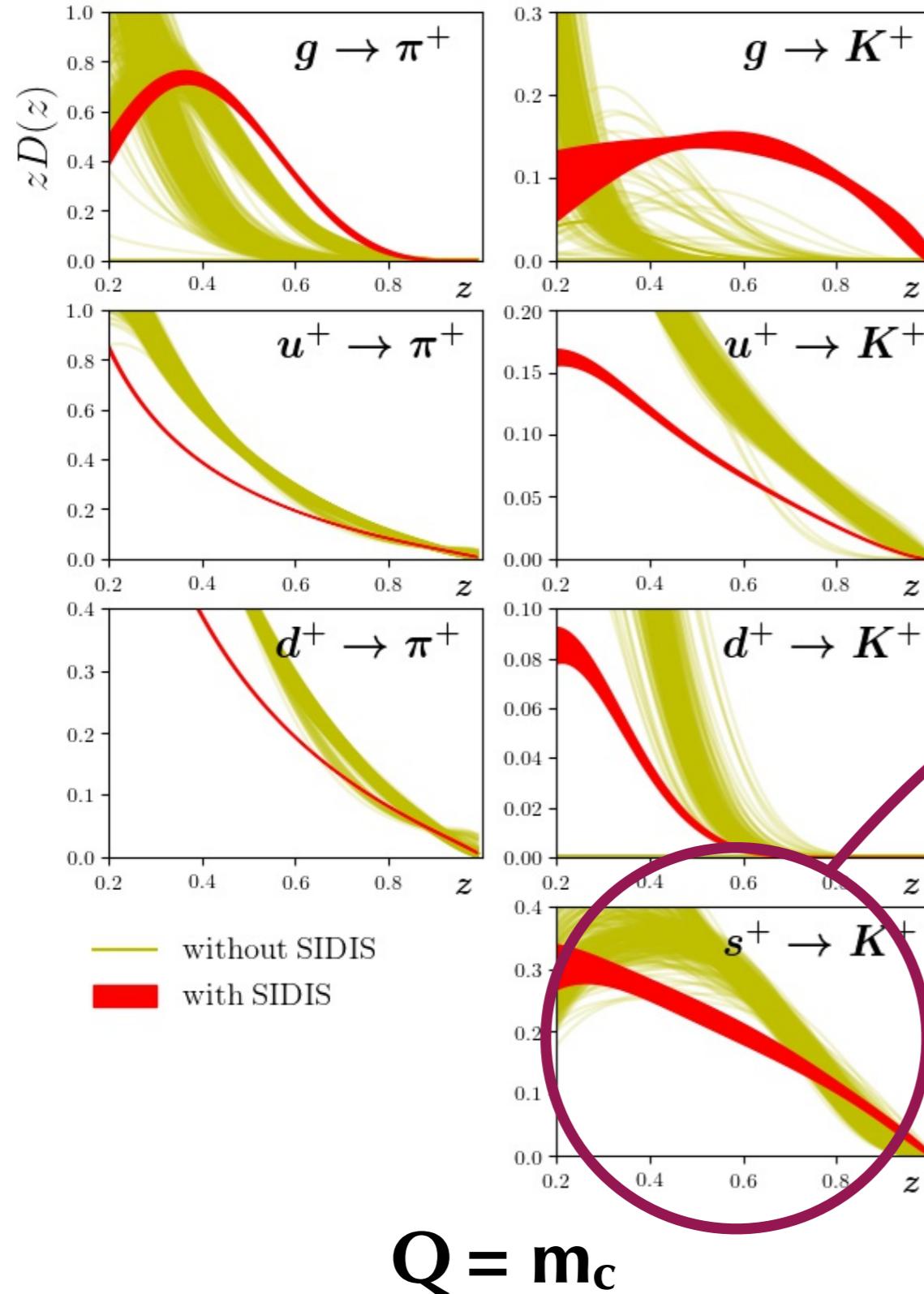
$$Q = m_c$$

Impact of SIDIS data on FFs



$Q = m_c$

Impact of SIDIS data on FFs

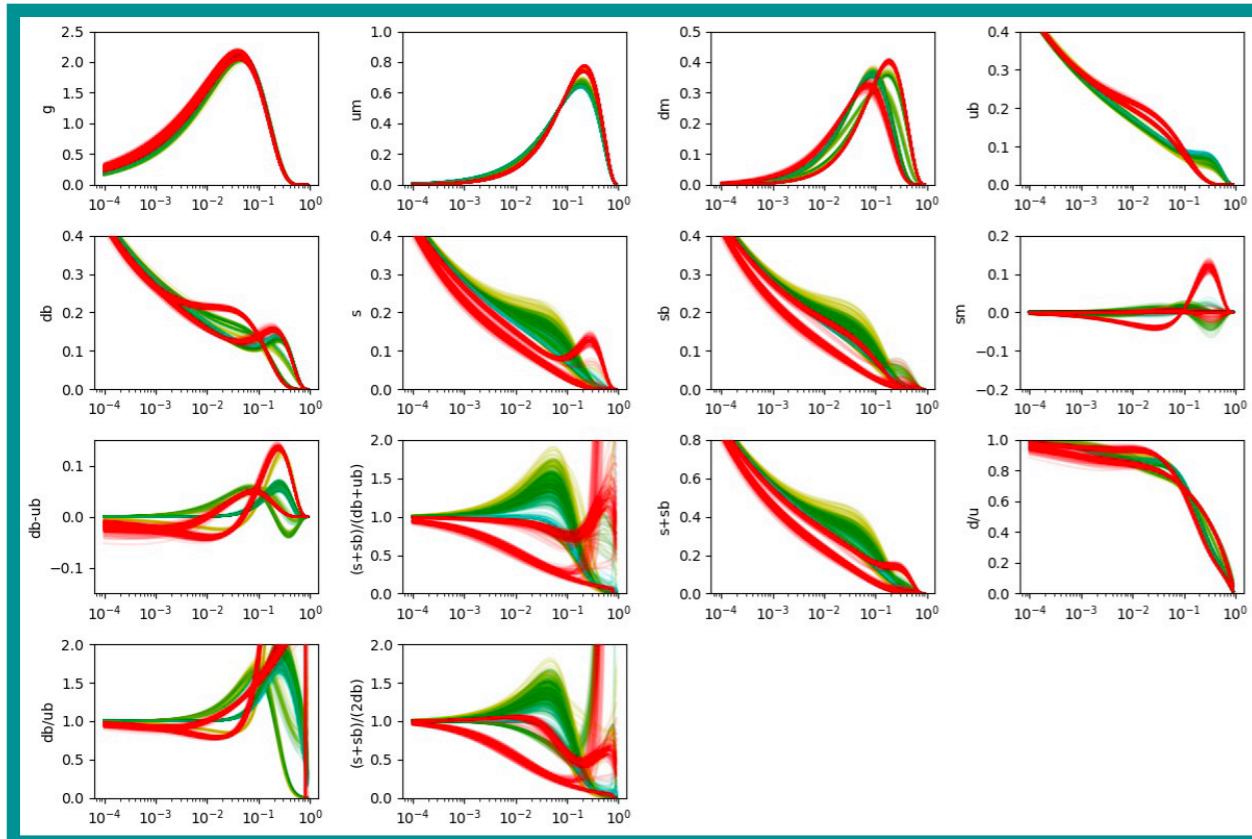


Constraints on
 $s^+ \rightarrow K^+$

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

Constraints on R_s

PDFs



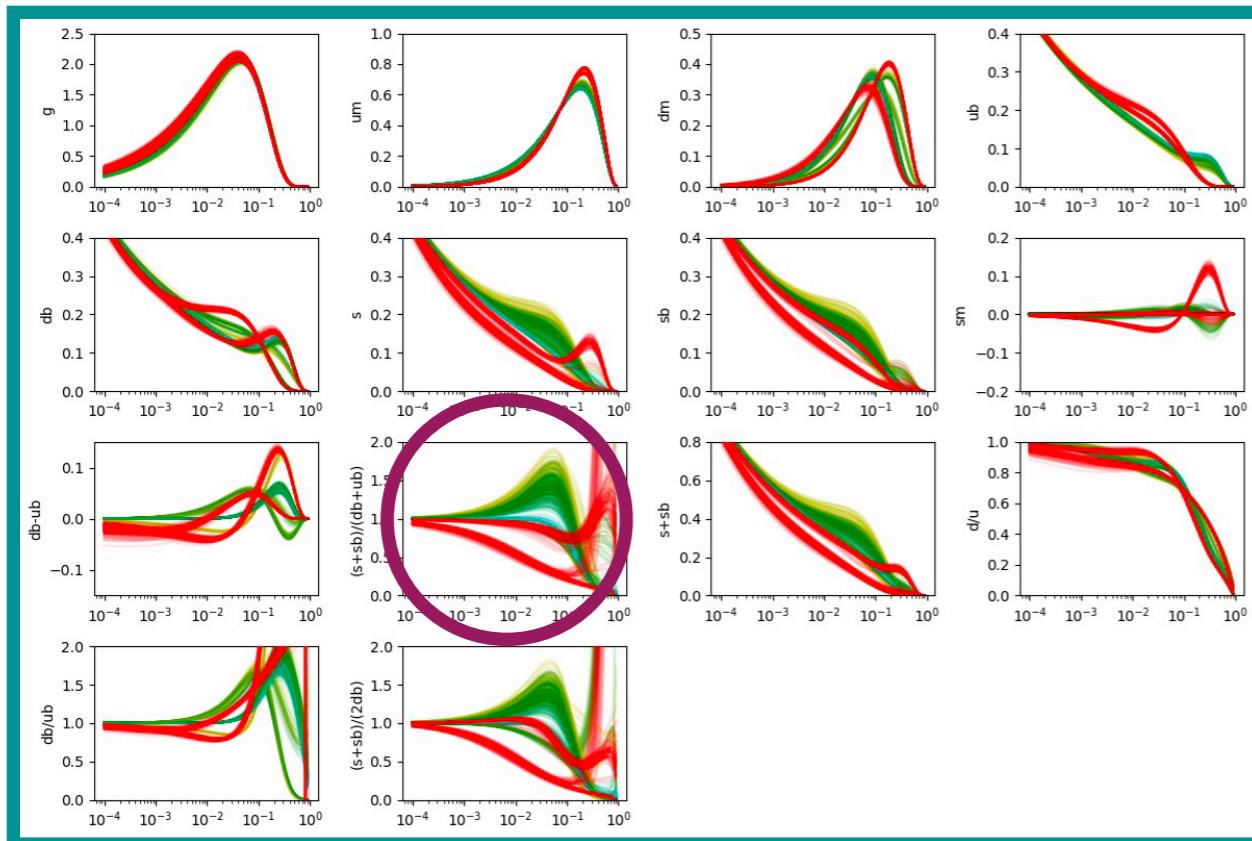
χ

+ DIS data

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

Constraints on R_s

PDFs



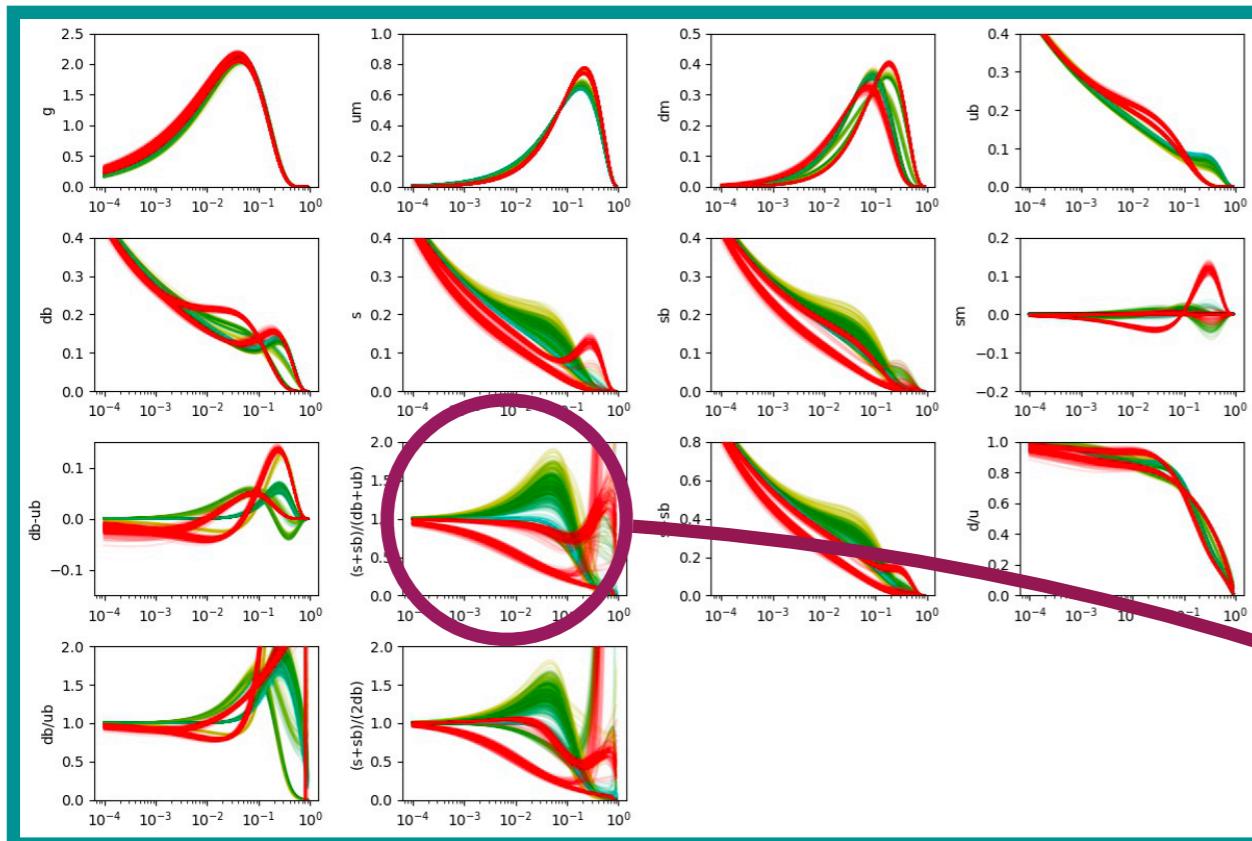
χ

+ DIS data

Constraints on R_s

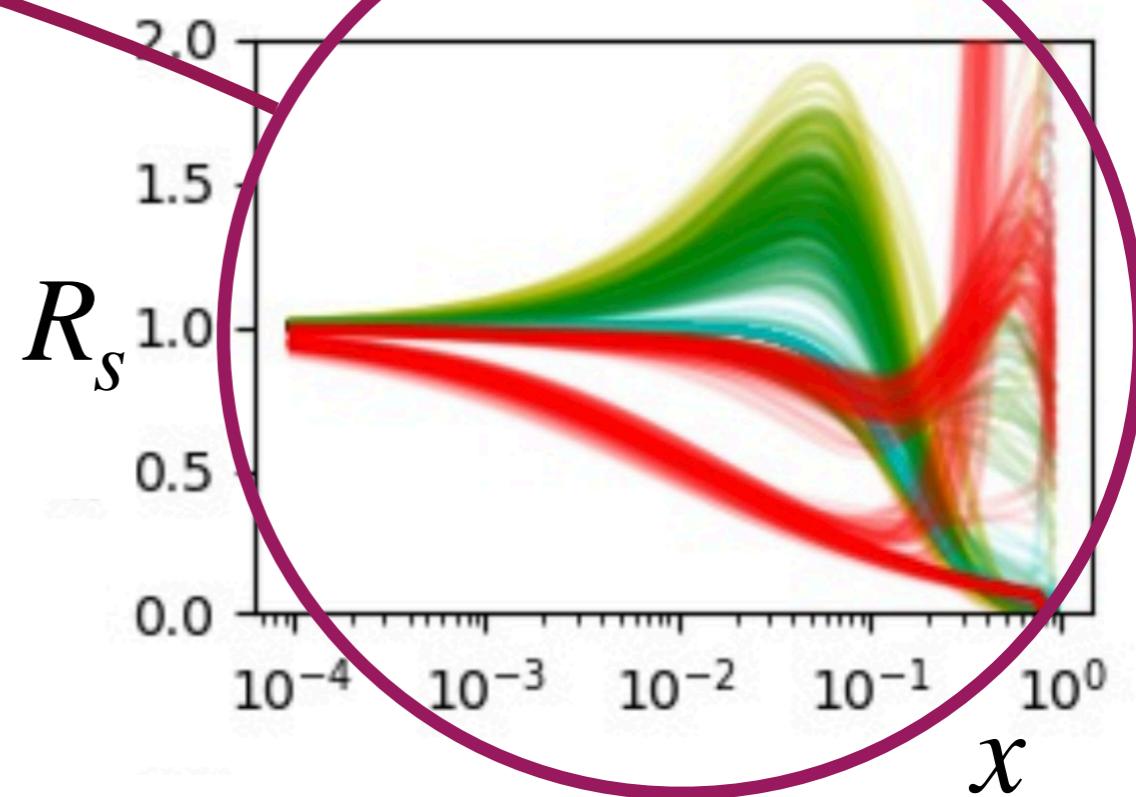
$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs



χ

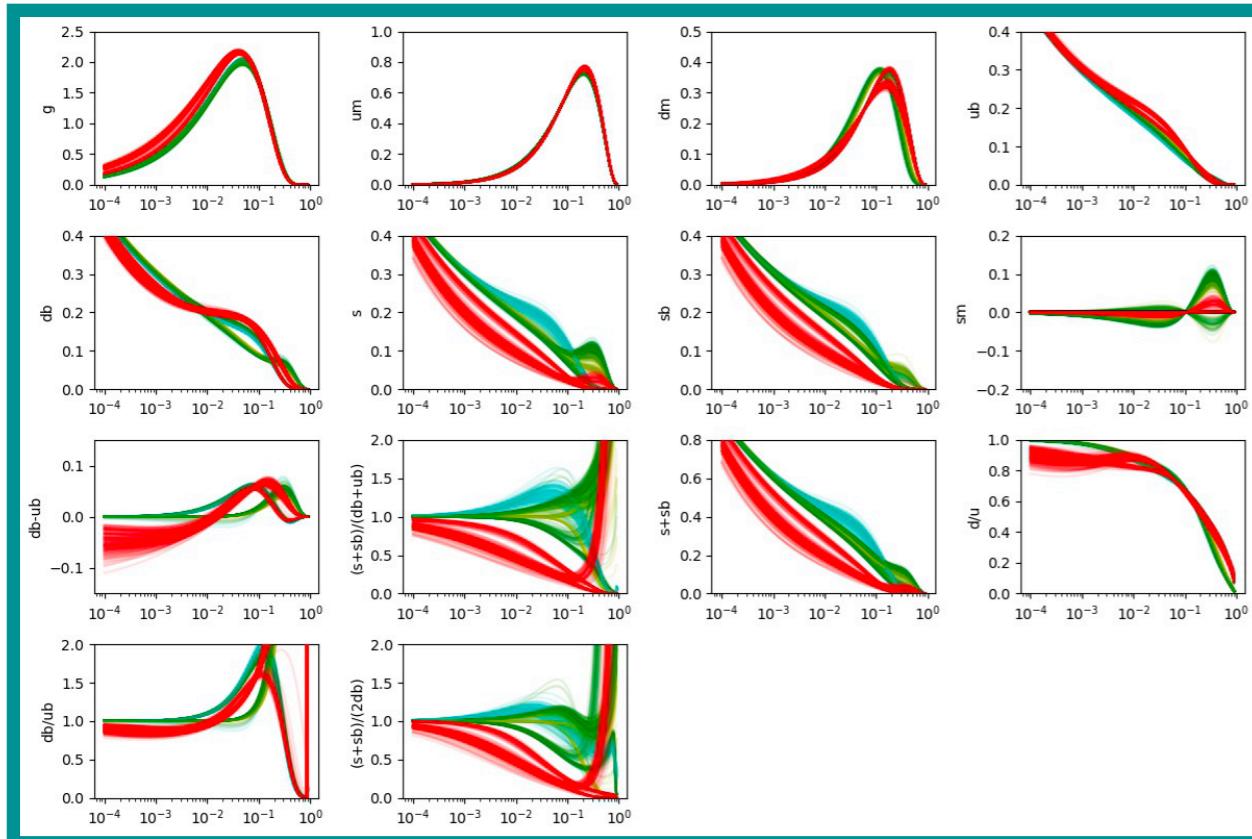
+ DIS data



Constraints on R_s

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs



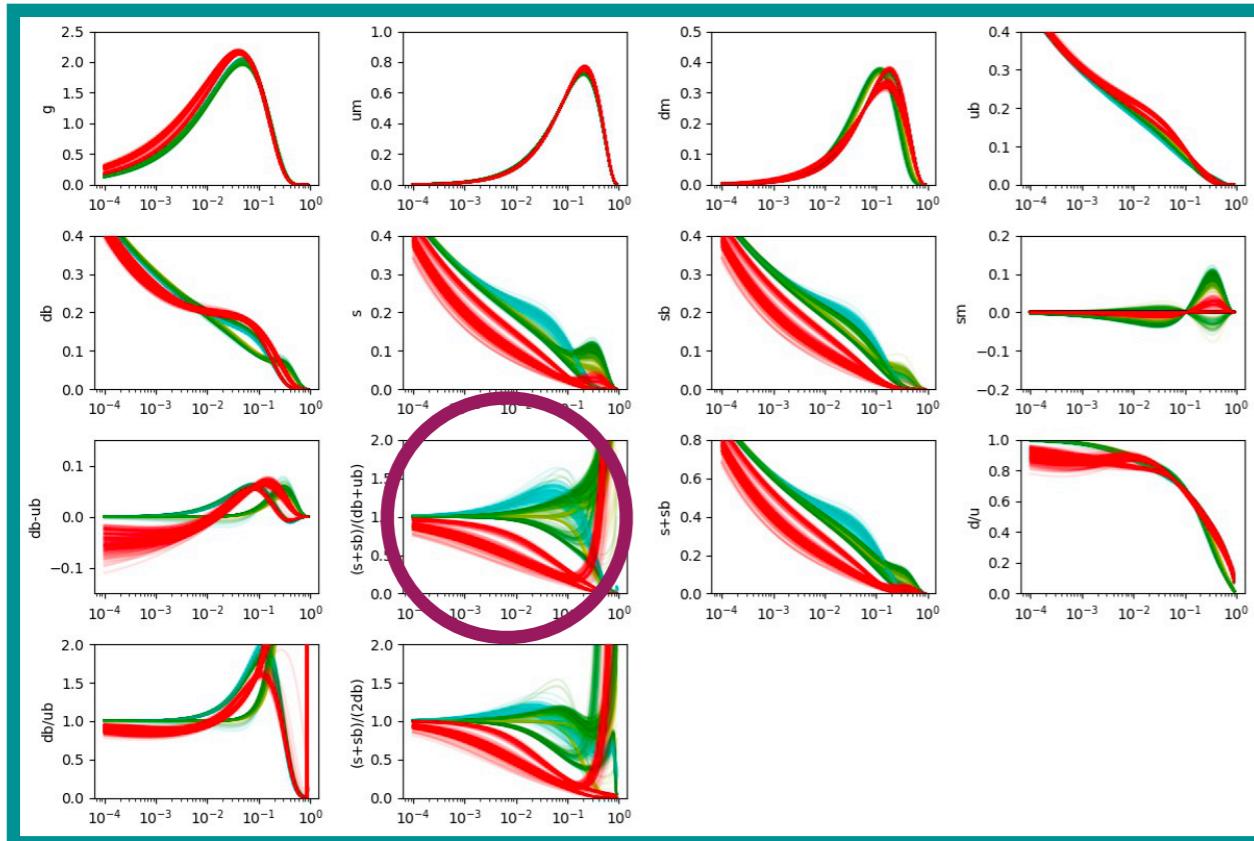
χ

+ DIS data
+ DY data

Constraints on R_s

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs



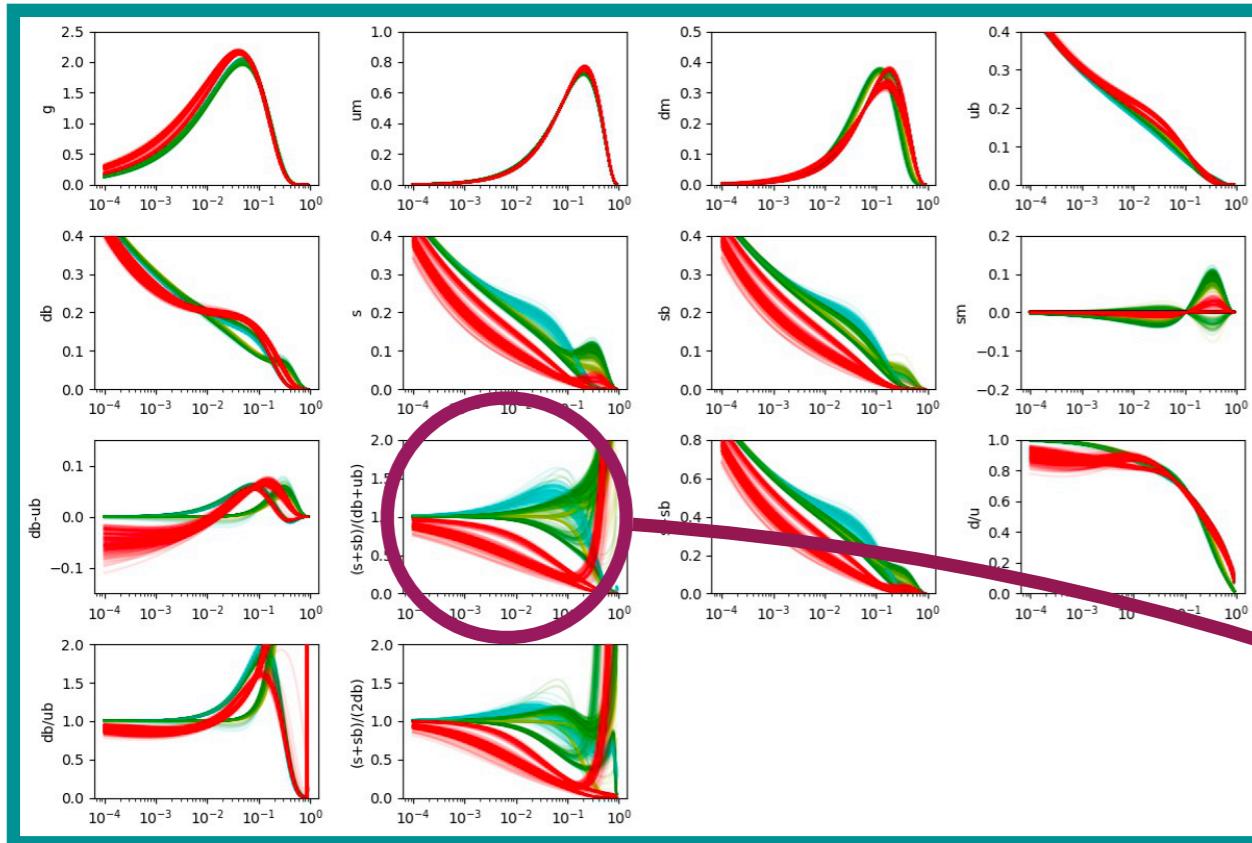
χ

+ DIS data
+ DY data

Constraints on R_s

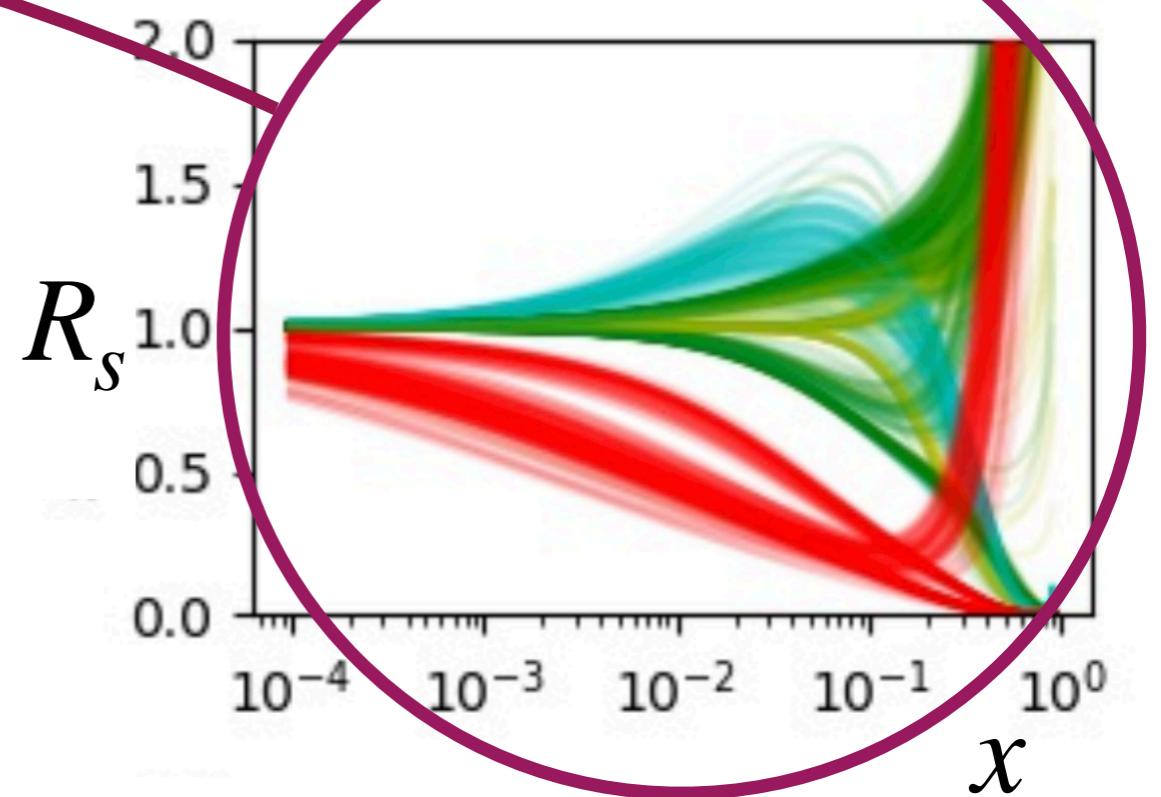
$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs



x

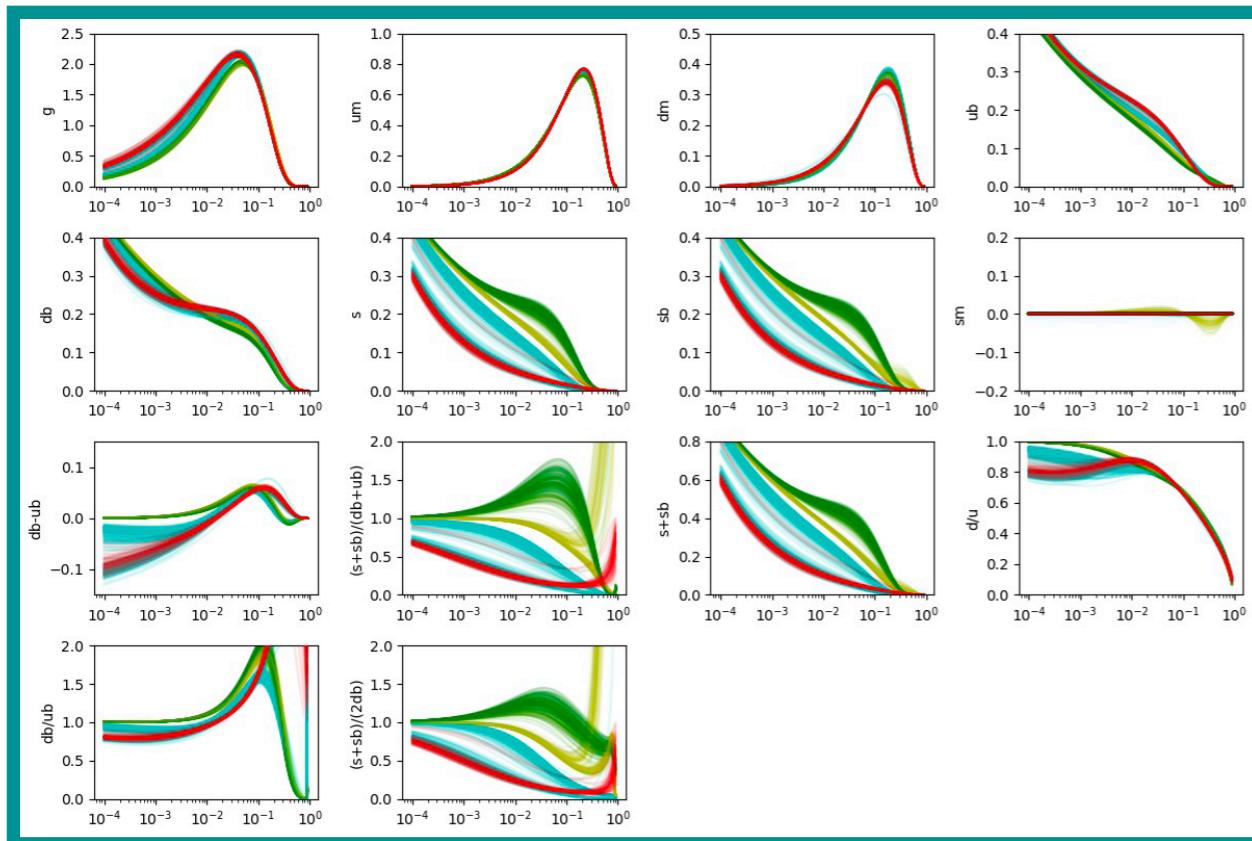
+ DIS data
+ DY data



Constraints on R_s

$$R_s = \frac{s + \bar{s}}{\bar{u} + d}$$

PDFs



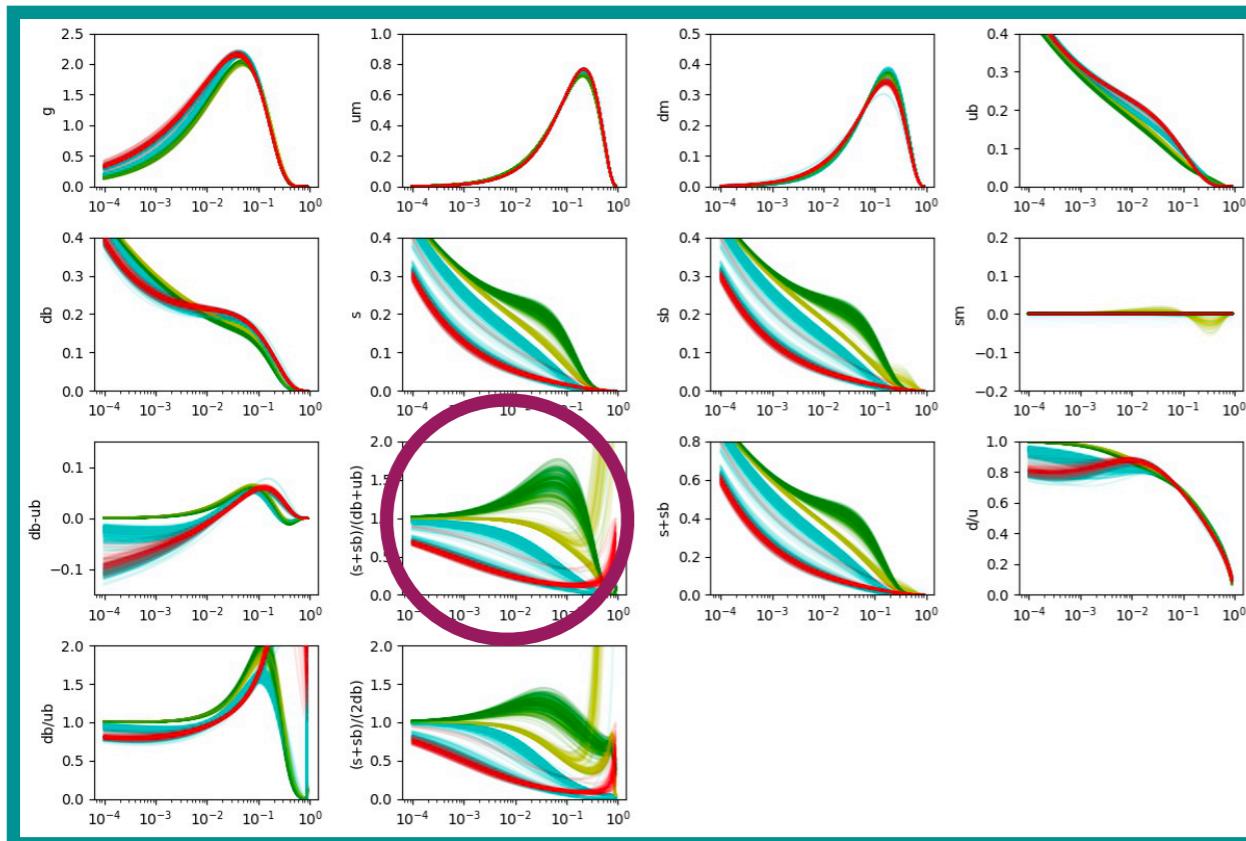
χ

- + DIS data
- + DY data
- + SIA + SIDIS data

$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

Constraints on R_s

PDFs



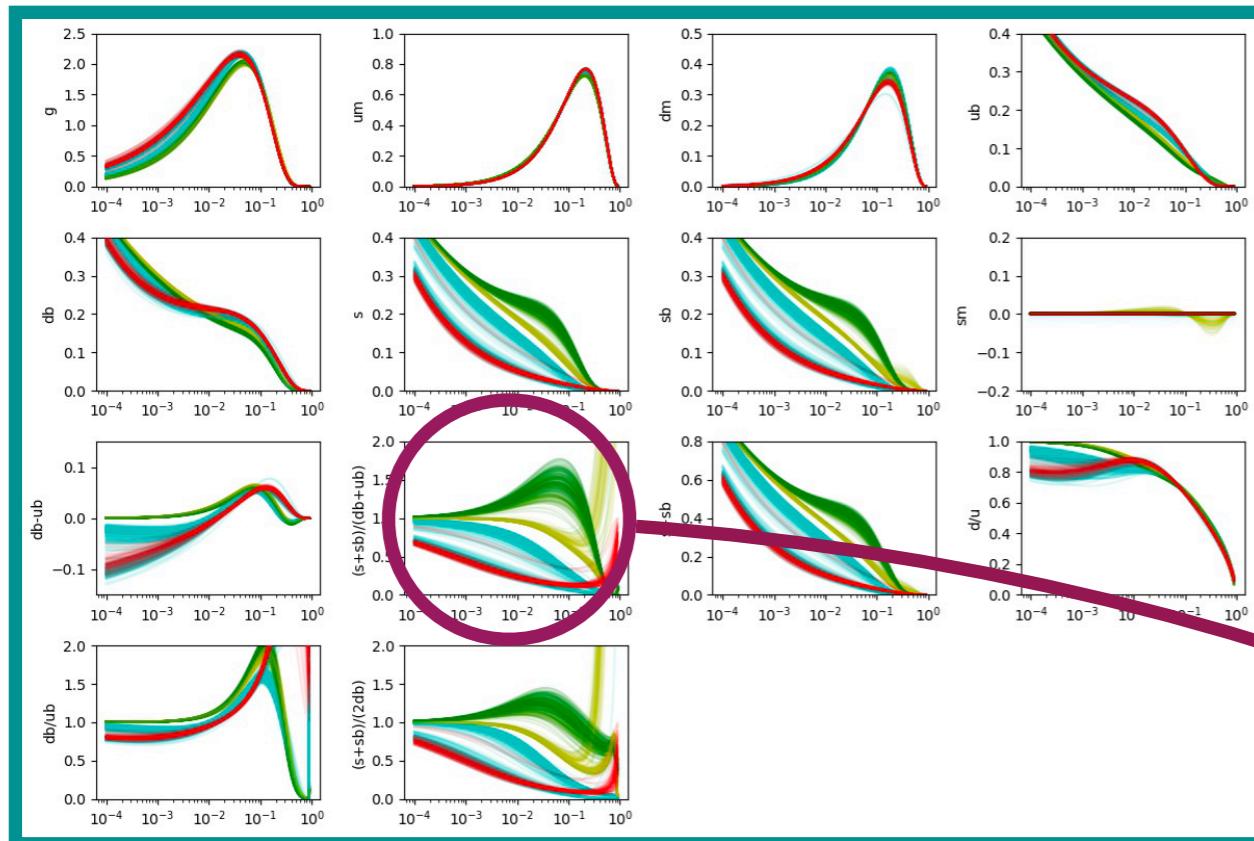
χ

- + DIS data
- + DY data
- + SIA + SIDIS data

Constraints on R_s

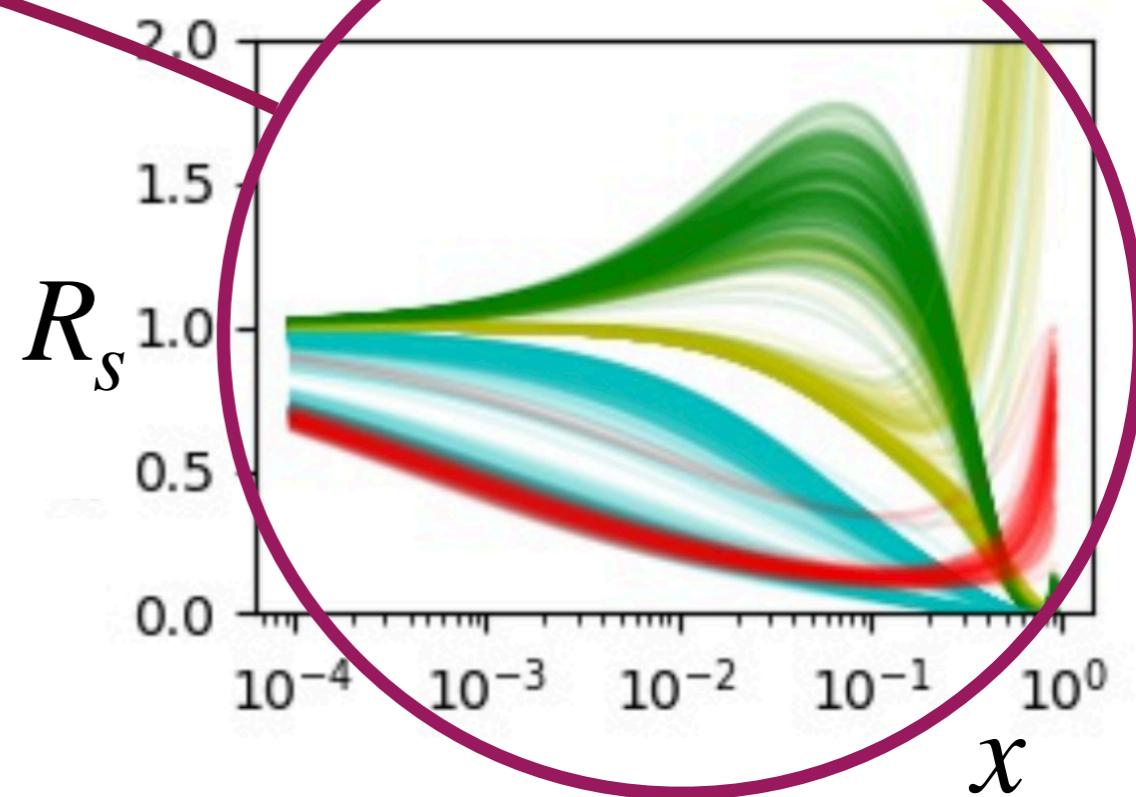
$$R_s = \frac{s + \bar{s}}{\bar{u} + \bar{d}}$$

PDFs



χ

- + DIS data
- + DY data
- + SIA + SIDIS data



Chi2

Reaction	N_{dat}	χ^2	χ^2/N_{dat}
SIDIS	992	1243.12	1.25
SIA	444	562.80	1.27
DIS	2680	3437.96	1.28
DY	250	416.29	1.67

Reaction	N_{dat}	χ^2	χ^2/N_{dat}
SIDIS (π^\pm)	498	585.48	1.18
SIDIS(K^\pm)	494	657.64	1.33
SIA(π^\pm)	231	247.27	1.07
SIA (K^\pm)	213	315.53	1.48

Experiment	target	hadron	N_{dat}	χ^2/N_{dat}
COMPASS	d	π^+	249	1.26
COMPASS	d	π^-	249	1.09
COMPASS	d	K^+	247	1.24
COMPASS	d	K^-	247	1.43